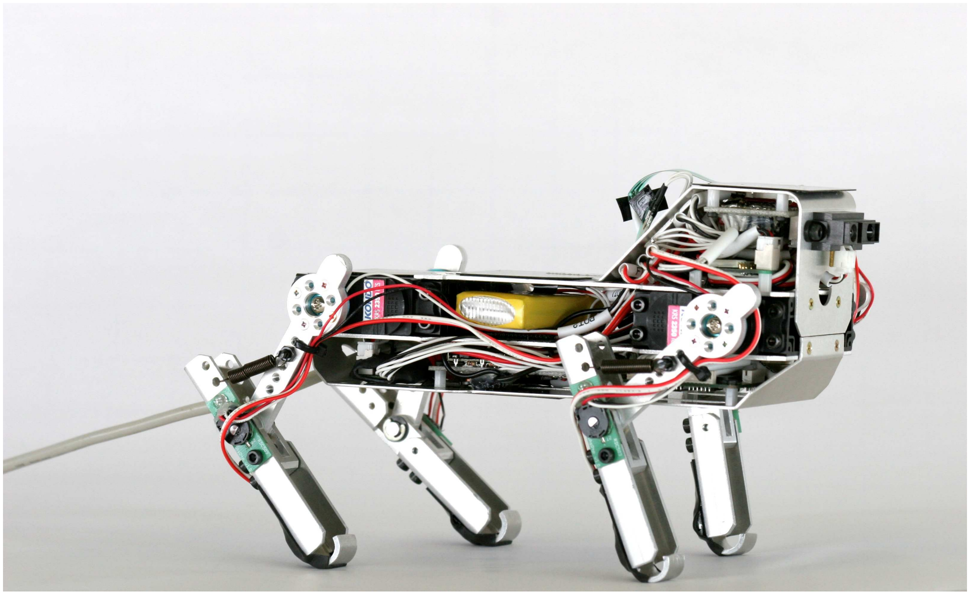
From Locomotion to Cognition

Bridging the gap between reactive and cognitive behavior in a quadruped robot



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Bridging the gap between reactive and cognitive behavior in a quadruped robot

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Abstract

The cognitivistic paradigm, which states that cognition is a result of computation with symbols that represent the world, has been challenged by many. The opponents have primarily criticized the detachment from direct interaction with the world and pointed to some fundamental problems (for instance the symbol grounding problem). Instead, they emphasized the constitutive role of embodied interaction with the environment. This has motivated the advancement of synthetic methodologies: the phenomenon of interest (cognition) can be studied by building and investigating whole brain-body-environment systems. Our work is centered around a compliant quadruped robot equipped with a multimodal sensory set. In a series of case studies, we investigate the structure of the sensorimotor space that the application of different actions in different environments by the robot brings about. Then, we study how the agent can autonomously abstract the regularities that are induced by the different conditions and use them to improve its behavior. The agent is engaged in path integration, terrain discrimination and gait adaptation, and moving target following tasks. The nature of the tasks forces the robot to leave the "here-and-now" time scale of simple reactive stimulus-response behaviors and to learn from its experience, thus creating a "minimally cognitive" setting. Solutions to these problems are developed by the agent in a bottom-up fashion. The complete scenarios are then used to illuminate the concepts that are believed to lie at the basis of cognition: sensorimotor contingencies, body schema, and forward internal models. Finally, we discuss how the presented solutions are relevant for applications in robotics, in particular in the area of autonomous model acquisition and adaptation, and, in mobile robots, in dead reckoning and traversability detection.

Zusammenfassung

Das kognitivistische Paradigma, welches besagt, dass Kognition aus dem Manipulieren (oder «Verrechnen») von die Welt repräsentierenden Symbolen resultiert, wurde von vielen angefochten. Die Gegner kritisierten hauptsächlich die Kluft zwischen der abstrakten Berechnung und der direkten Interaktion mit der Welt und zeigten grundlegende Probleme auf (zum Beispiel das «Symbol Grounding Problem»). Stattdessen hoben sie die konstitutierende Rolle der «embodied» («verkörperten») Interaktion mit der Umwelt hervor. Dies hat die Weiterentwicklung synthetischer Methodologien motiviert: Das zu untersuchende Phänomen (Kognition) lässt sich studieren, indem umfassende Gehirn-Körper-Umgebungs-Systeme gebaut und untersucht werden. Unsere Arbeit dreht sich um einen nachgiebigen vierbeinigen Roboter, der mit einem multimodalen Sensorium versehen ist. In einer Reihe von Fallstudien untersuchen wir die Struktur des sensomotorischen Raums, der von der Anwendung des Roboters in verschiedenen Aufgaben und unterschiedlichen Umgebungen aufgespannt wird. Anschliessend erforschen wir, wie der Agent aus unterschiedlichen Rahmenbedingungen selbständig Regularitäten abstrahieren kann, und benutzen diese, um sein Verhalten zu verbessern. Der Agent führt Pfadintegration durch, unterscheidet Gelände-Typen, passt seine Gangart an und folgt sich bewegenden Zielen. Die Eigenschaften dieser Aufgaben zwingen den Roboter dazu, die «Hier-und-jetzt»-Perspektive eines einfachen reaktiven Stimulus-Respons-Verhaltens zu verlassen und aus seiner Erfahrung zu lernen, wodurch eine «minimal kognitive» Situation entsteht. Lösungen zu diesen Aufgaben werden vom Agenten im Bottom-Up-Verfahren entwickelt. Die kompletten Szenarien werden dann benutzt, um diejenigen Konzepte zu illustrieren, welche wir als grundlegend für Kognition vermuten: Sensorimotorische Kontingenzen, Körperschema und Vorwärtsmodelle. Schliesslich diskutieren wir die Relevanz der aufgezeigten Lösungen für Anwendungen in der Robotik, insbesondere im Bereich der autonomen Modellbildung und Modellanpassung und – in der mobilen Robotik – für Koppelnavigation und um zu detektieren, ob ein bestimmtes Terrain überquert werden kann.

Contents

Preface

"What does walking have to do with thinking?" "Very little," would be the answer of the proponents of the cognitivistic paradigm in cognitive science. To them (e.g., [Fodor, 1975, Pylyshyn, 1984]), thinking is understood as a result of computation over symbols that represent the world. Walking, on the other hand, may be looked at as very low-level, simple, physical and, therefore, uninteresting with regard to the study of cognition.

More recently, the view of cognition as symbolic computation has been challenged, and an embodied, action-oriented, dynamic, and developmental view has been proposed instead (e.g., [Varela et al., 1991, Thelen and Smith, 1994, Pfeifer and Bongard, 2007]). The boundaries between cognitive and non-cognitive phenomena have started to blur and the key influence of the body and the physical interaction with the environment has become accepted. Furthermore, a central role of developmental processes in the emergence of cognition has been asserted. There is growing and increasingly detailed evidence from psychology and neurosciences in support of the *embodied cognitive science* view. However, the premises of the new paradigm—whole brain-body-environment systems should be studied over extended time periods—pose new challenges to practical empirical research in animals and humans. Here, synthetic methodology, i.e. instantiating and studying the phenomena of interest in robots, can serve as a viable tool to verify certain hypotheses and complement the research in psychology and neuroscience.

In this thesis, we deploy the synthetic methodology in a quadruped robot and investigate the possibilities of its autonomous development from "walking" to "thinking", in other words, from locomotion to cognition. The case studies presented feature the key ingredients that are believed to be necessary for cognition to emerge: rich body dynamics and physical interaction with different environments, active generation of multimodal sensory stimulation and learning from this experience over different time scales. The scenarios are chosen such that they can be successfully mastered only if the robot leaves the "here-and-now" time scale of reactive, stimulus-response, behaviors. In order to do that, the robot needs to extract some regularities from its interaction with the environment and apply this knowledge when selecting the next actions to take. To this end, we will explore three concepts that were proposed to explain the development and operation of minimal instances of cognition: body schema (e.g., [Holmes and Spence, 2004, de Vignemont, 2010]), forward internal models (e.g., [Webb, 2004, Franklin and Wolpert, 2011]), and sensorimotor contingencies [O'Regan and Noe, 2001]. A concrete implementation in the robot will help us to better understand the meaning of each of them as well as hint at their potential role in early cognitive development.

The locomotion context is particularly suited to understanding minimally cognitive behavior. Whereas "manual cognition", i.e. reaching, grasping and dexterous manipulation, is largely restricted to humans and primates, "locomotor cognition", on the other hand, can be found in much lower animals. For example, path integration was discovered in ants [Wittlinger et al., 2006]; prediction was demonstrated in motor preparation of prey-catching behavior of a jumping spider [Schomaker, 2004]; frogs were found to be able to predict whether an aperture could be passed [Collett, 1982]; finally, rats were found covertly comparing alternative paths in a T-maze, thus "planning in simulation" [Hesslow, 2002]. In this work, we will present the robot with similar scenarios: path integration, terrain discrimination and gait selection, and catching another robot.

In addition, allowing robots to autonomously develop their control architecture (that is not just fine-tune a previously designed controller) bears enormous application potential, possibly leading to truly adaptive and resilient machines that will be able to leave controlled environments. The case studies presented address autonomous self-model synthesis, autonomous navigation, terrain discrimination and adaptation, and, finally, planning and interaction with another robot.

This dissertation is structured as follows. The introductory chapter provides a survey of the theories of cognition, introduces synthetic methodology, reviews related application areas in robotics, and presents the approach to cognition adopted in this thesis. The essence of this dissertation consists of five case studies on a mobile robot that constitute a "from locomotion to cognition" roadmap. In Chapter 2, the case studies and their relationship to minimally cognitive phenomena is overviewed. Chapters 3 to 7 summarize the main contributions of individual case studies to the overarching goals of this thesis. We conclude with a discussion, a summary of contributions, limitations, and future research agenda (Chapter 8). In the Appendices, we enclose seven peer-reviewed scientific publications that are an integral part of this dissertation. Appendix A and B provide a comprehensive overview of the background and related work on the implications of embodiment and body schema. Appendices C to G are full descriptions of the case studies abstracted in Ch. 3 to 7.

Chapter 1

Introduction

Our main goal in this chapter will be to briefly sketch the different approaches to the study of cognition, point out their assumptions, advantages and limitations, and explain what is the stance adopted in our work. We will start by briefly recapitulating the cognitivistic paradigm that focuses on algorithmic implementation of high-level cognitive functions (reasoning, planning, etc.). There, the instantiation of this "cognitive algorithm" in an agent (human, animal, robot) is of marginal importance. This stance was attacked from different disciplines and viewpoints, but each of them asserted the key involvement of the body and embedding in the environment in shaping cognitive processes. A radical example is behavior-based robotics, which we will review next. There, physical interaction with the environment, rather than internal representations and computation over them, is the central theme. Although some remarkable behaviors emerged, the complexity of the tasks that these creatures could master was limited. Therefore, our main focus will be to investigate how these simple agents could build on top of their basic capabilities by developing simple mechanisms that we could call cognitive. Under the "embodied cognition" umbrella (section 1.3), we will review the theories of grounded cognition, simulation theory, the enactive and dynamical systems viewpoint. In section 1.4, we will introduce the synthetic methodology—understanding phenomena through building artifacts—and continue with an account of the role that development plays in the emergence of cognition. Then we will review the concepts of body schema, forward internal models and sensorimotor contingencies, which will serve as minimally cognitive building blocks in our explorations. The theories of cognition will be complemented by discussing the implications that our work has for increasing the autonomy of robots (section 1.7). Finally, we will wrap up and present the approach to cognition adopted in this thesis.

Nevertheless, to facilitate the reader's orientation in the "cognitive landscape", we will start off with the basic premises that Vernon et al. [Vernon et al., 2010b] have put forth and that characterize our viewpoint as well:

- Cognition is the process by which an autonomous self-governing agent acts effectively in the world in which it is embedded.

- The dual purpose of cognition is to increase the agent's repertoire of effective actions and its power to anticipate the need for an outcome of future actions.

- Development plays an essential role in the realization of these cognitive capabilities.

1.1 Cognitivism and GOFAI

The initial foundations of cognitive sciences were laid down by cognitivism (e.g., [Fodor, 1975, Pylyshyn, 1984]).[1] The aspects of intelligence or cognition that were modeled were the high-level cognitive functions, such as problem-solving, representation of knowledge and reasoning, and planning. The essence of this paradigm is that the key to intelligence is computation with symbols that represent the world. The keywords are *algorithmic nature, symbolic computation and representation*. Newell and Simon put forth the Physical Symbol Systems Hypothesis [Newell and Simon, 1976] which states, in essence, that a physical symbol system has the necessary and sufficient means for intelligent action. The body is thus of marginal importance here, it can be any physical system (e.g., Emmental cheese) as long as it can perform the same function—the right computation on symbols. The cognitivist paradigm is thus also known as *functionalism* [Putnam, 1975]. Although, in theory, the physical machinery can be arbitrary, the field has quickly adopted one dominant platform to run the computation over symbols: a digital computer. This has had far-reaching implications, since the computer was not only the tool on which these models could run, but also quickly became the leading *metaphor for mind*.

The strand of AI that was adopting but at the same time co-defining the cognitivistic paradigm became known as "Good Old-Fashioned Artificial Intelligence" (GOFAI) [Haugeland, 1985]. It was and is very successful in formal domains (such as formal games like chess). There, the state of the world is discrete and directly accessible and standard AI techniques (like searching) can be applied. While the focus has been on abstract "thinking", when entering the real world, a relationship had to be established between the dynamic, continuous, partially accessible reality out there and the internal world representation (see [Pfeifer and Scheier, 2001, p. 58] for a discussion of real vs. virtual worlds). That is the reality had to be sensed and mapped onto the internal world model, in which the "thinking" was performed. Finally, whatever action was selected, it had to be executed in the real world. The approach thus became known as the *sense-think-act* architecture. The "interfaces" with the real world—previously uninteresting and underestimated—became the source of fundamental as well as practical problems. The "frame problem" (keeping the internal representation of the world consistent with the real world outside) and the "symbol-grounding problem" (concerned with the relationship of the symbolic representation and the outside world) are the most serious of the former. The interested reader is referred to [Pfeifer and Scheier, 2001, p. 65-71] for a review. We will discuss how these problems are faced by the robotic systems of today in section 1.7.1.

1.2 Behavior-based robotics – intelligence without representation

A somewhat radical alternative was offered by behavior-based robotics. In order to demonstrate that behaviors, which would be considered intelligent or cognitive by many, do not have to come from internal world models and computation over them, machines with minimalistic controllers were built and their interaction with the environment was observed. Grey Walter [Walter, 1953] was the pioneer of this approach, building electronic machines with a minimal "brain" that displayed phototactic-like behavior. This was picked up by Valentino Braitenberg [Braitenberg, 1986] who built a whole series of two-wheeled vehicles of increasing complexity. Already the most primitive ones, in which sensors are directly connected to motors (exciting or inhibiting them),

[1] This paragraph is based on our account in [Hoffmann et al., 2011a], `http://www.eucognition.org/index.php?page=cognitivism`, retrieved 28.3.2012.

display sophisticated behaviors. Although the driving mechanisms are simple and entirely deterministic, the interaction with the real world gives rise to complex behavioral patterns.

Rodney Brooks has openly attacked the GOFAI position in the seminal articles "Intelligence without representation" [Brooks, 1991b] and "Intelligence without reason" [Brooks, 1991a]. Through building robots that interact with the real world, such as insect robots [Brooks, 1989], he realized that "when we examine very simple level intelligence we find that explicit representations and models of the world simply get in the way. It turns out to be better to use the world as its own model." [Brooks, 1991b] Inspired by biological evolution, Brooks created a decentralized control architecture consisting of different layers; every layer is a more or less simple coupling of sensors to motors. The levels operate in parallel, but are built in a hierarchy (hence the term *subsumption architecture* [Brooks, 1986]). The individual modules in the architecture may have internal states (the agents are thus not purely reactive anymore), however Brooks argues against calling the internal states representations [Brooks, 1991b].[2] In summary, Brooks has proposed that a change of focus in AI is necessary: insect-level not human-level intelligence is the hard problem that evolution has spent the most time on and this should apply to Artificial Intelligence as well.

The thesis that intelligent behavior emerges from the dynamic interplay of brain, body and environment has also been articulated by the notion of *embodiment* (e.g., [Pfeifer and Scheier, 2001, Pfeifer et al., 2007]). One can study even lower-level behaviors than those that we have looked at above (where complex behavior arises from simple direct feedback connections) and demonstrate that even completely brain-less, purely mechanical, creatures are already capable of behavior. A powerful illustration of this concept is the passive dynamic walker [McGeer, 1990]. Furthermore, even artifacts that do not have any neural feedback can demonstrate simple adaptive behavior in the form of robustness to perturbations. This is achieved through mechanical feedback and has been called self-stabilization (e.g., [Blickhan et al., 2007]). We have analyzed these and other case studies on locomotion and grasping in [Hoffmann and Pfeifer, 2011]. This publication is attached in Appendix A; please refer to the sections "Physical implications of embodiment in locomotion" and "Physical implications of embodiment in grasping".

In summary, the body of work we have reviewed in this section focuses on low-level behaviors and demonstrates that these do not rely on representations and computation, but rather on complex dynamic interaction of bodies with the environment and on simple, loosely coupled, sensorimotor feedback loops. This strand of AI became known as "Behavior-based robotics" or "New AI". However, unlike GOFAI which has set out to understand and synthesize higher cognitive processes from the beginning, "New AI" has, deliberately, remained at a "pre-cognitive" level. The critics therefore object that the approach does not scale up and that higher-level intelligence is needed for the artifacts to be useful. This criticism is justified. Therefore, the challenge lies in naturally extending the behavior-based approach by letting the agents learn from their experience and acquire internal mechanisms that will allow them to act more effectively in the future (by being able to predict the outcome of their actions, for instance). At the same time, the merits of the behavior-based approach—firm grounding in the interaction with the environment—should not be given up.

1.3 Embodied cognition

The embodied cognition viewpoint in general holds that cognitive processes are constitutively shaped by the interaction with the world through the agent's body. That is, unlike in (computer) functionalism that we have reviewed in section 1.1, different embodiments give rise to different

[2]Clearly, there is no central representation in the system. At most, these states correlate with some situations in which the agent (that is not just its brain!) finds itself, which could be labeled an implicit representation by some.

cognitive processes. However, a large number of different theories falls under this very broad statement. We will analyze some of them below.

1.3.1 Grounded cognition and simulation theory

A number of researchers from different disciplines has been dissatisfied with the notion of computation over detached symbolic representations and the resulting grounding problem that characterize cognitivist systems (section 1.1). To resolve this, they have looked for evidence to demonstrate the tight relationship between high-level cognitive processes and low-level sensorimotor and bodily processes.

The most successful in the quest for grounding cognition have been the simulation theories. Barsalou [Barsalou, 2008] has characterized simulation as follows:

> Simulation is the reenactment of perceptual, motor, and introspective states acquired during experience with the world, body, and mind. As an experience occurs (e.g., easing into a chair), the brain captures states across the modalities and integrates them with a multimodal representation stored in memory (e.g., how a chair looks and feels, the action of sitting, introspections of comfort and relaxation). Later, when knowledge is needed to represent a category (e.g., chair), multimodal representations captured during experiences with its instances are reactivated to simulate how the brain represented perception, action, and introspection associated with it.

Simulation thus has the important property that patterns that the agent has experienced can be retrieved and run covertly, "offline". According to Barsalou [Barsalou, 2008], simulation mechanisms are present across diverse cognitive processes, suggesting that simulation provides a core form of computation in the brain. A well-studied example is mental imagery (e.g., [Kosslyn, 1994, Kosslyn et al., 2006]). Computation in the brain thus proceeds in the modal space—space of motor and sensory modalities—rather than amodal (modality-independent) space. The existence of amodal symbols (perhaps with the exception of language processing) is questioned [Barsalou, 2008]. Nevertheless, in his Perceptual Systems Theory (PSS), Barsalou [Barsalou, 1999] demonstrates that even standard symbolic functions (type-token binding, inference, productivity, recursion, propositions) could be implemented using simulation and dynamic systems.

This viewpoint is appealing because it offers a compromise between the traditional cognitivist paradigm and the embodied stance. Clark and Grush [Clark and Grush, 1999] have characterized cognitive agents as follows:

> Cognizers, on our account, must display the capacity for environmentally decoupled thought and the contemplation of options. The cognizer is thus the being who can think or reason about its world without directly engaging those aspects of the world that its thoughts concern.

The offline reasoning capability ("environmentally decoupled thought") that they use to demarcate cognitive agency is seamlessly provided by the simulation framework. They argue that simulator (or emulator[3]) circuitry is an internal *representation* of extra-neural (e.g., bodily) states of affairs. The advantage is that the simulator can be instantiated at different levels of complexity. The simplest form is a forward model that provides the prediction of a future sensory state given the current state and a motor command (we will give more details in section 1.6.3). This is, according to [Clark and Grush, 1999], a possible explanation of the evolutionary origin of off-line reasoning—the agent employing primitive "models" before or instead of directly operating on the world.

[3]Cf. [Grush, 2004] for the similarities and differences between emulation theory [Grush, 2004] and simulation theory [Jeannerod, 2001].

> How did internal representation (in a strong sense, still to be defined) ever get its foot in the door of real-world, realtime cognition? The answer, we speculate, is that world-modeling got its foothold when nature discovered that emulator circuitry could improve real-world, real-time responsiveness. With that circuitry on hand (so to speak) it probably required only minor cheap modifications to glean the added benefits available from running the emulator completely off-line so as to aid planning, support mental imagery, and so on. Early emulating agents would then constitute the most minimal case of what Dennett calls a Popperian creature—a creature capable of some degree of off-line reasoning and hence able (in Karl Popper's memorable phrase) to "let its hypotheses die in its stead" [Dennett, 1995, p. 375]. [Clark and Grush, 1999]

The simulator circuitry can be trained from past experience: by executing the behavior overtly, the training signals for the simulators are provided. Then, this circuitry can be used for future-oriented behavior: to predict future sensory states or internally "rehearse" whole courses of actions and their consequences. Thus, it can become a key to the anticipatory capabilities of a cognitive agent which are believed to play a crucial rule in all cognitive phenomena (cf. [Bar, 2009] for a review of evidence from neurosciences and [Pezzulo et al., 2008] for a survey of different architectures as well as studies in artificial systems).[4]

The "representationalist" interpretation [Clark and Grush, 1999] brings up the question whether this will bring us back to cognitivism—the representation-based paradigm—and the problems associated with it. Clark and Grush [Clark and Grush, 1999] argue that the emulator circuitry may act as a bridge between the real-world, real-time, non-representationalist focus of the work in behavior-based robotics (section 1.2) and the traditional cognitivist focus on inner models and decoupled reasoning. In this case, the representations have a different nature than the GOFAI representations. Rather than representing static features (such as objects), dynamic interaction patterns, which involve the robot acting in the environment, are represented. Such representations are best viewed as motor-based. They are action-oriented, egocentric, originate in the sensory-motor apparatus and remain intimately related with it [Clark and Grush, 1999, Pezzulo, 2007].

1.3.2 Enaction, dynamical systems, and the extended mind

In a nutshell, one could summarize the previous section by saying that cognition is a result of computation performed on representations in the brain, but the computation and representations have a dynamic, often multimodal nature, and they are acquired through and grounded in embodied interaction with the environment. However, there are schools of embodied cognition that reject this representation-based approach, which rests on the "detached contemplation" possibility, altogether. In addition, the brain as the sole seat of cognition is questioned.

Enaction

A unique perspective on cognition has been offered by the community that has grown around the work of Francisco Varela (e.g., [Varela et al., 1991]). The proponents of the *enactive framework* reject the idea that "cognition often proceeds independently of the body" [Barsalou, 2008]. For the "enactivists", cognition is not only shaped by the body and its action possibilities, but *cognition is action*—embodied action, a form of practice itself [Varela et al., 1991]. In this view, cognition is not about world-mirroring through representations, but "world-making" and sense-making.

[4] In fact, some researchers would equate this general capacity with *memory*. Berthoz [Berthoz, 2000, p. 115] puts it: "Memory is used primarily to predict the consequences of future action by recalling those of past action." [Wood et al., 2012] also defined memory as "The capacity to use previous experience to inform subsequent behavior."

The interested reader is referred to the abundant literature (e.g., the recent collection of papers in [Stewart et al., 2010], reviewed in [Froese, 2012], or [Vernon, 2010] where enaction is presented as a framework for cognitive robotics).

Dynamical systems, extended mind

In section 1.2, we have discussed that behavior is not "in the brain", but is a result of a dynamic interaction of the brain, body and environment. This thesis can be applied to cognition as well:

> Cognitive processes span the brain, the body, and the environment: to understand cognition is to understand the interplay of all three. Inner reasoning processes are no more essentially cognitive than the skillful execution of coordinated movement or the nature of the environment in which cognition takes place. [Port and van Gelder, 1995]

A conceptual framework as well as analytical machinery in line with this view is provided by the *dynamical systems view*: cognitive agents are best understood as dynamical systems and the tools of the mathematical theory of dynamical systems can be applied to analyze them (e.g., [Beer, 1995, Beer, 2003, Thelen and Smith, 1994, Port and van Gelder, 1995]. Thompson [Thompson, 2007, pp. 10-13] has used the term *embodied dynamicism* to label this approach.

The same thesis—cognition is continuous with processes in the environment—has been also articulated by the *Extended mind hypothesis* [Clark and Chalmers, 1998]:

> ... the human organism is linked with an external entity in a two-way interaction, creating a coupled system that can be seen as a cognitive system in its own right. All the components in the system play an active causal role, and they jointly govern behavior in the same sort of way that cognition usually does. If we remove the external component the system's behavioral competence will drop, just as it would if we removed part of its brain. Our thesis is that this sort of coupled process counts equally well as a cognitive process, whether or not it is wholly in the head.

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This approach is further elaborated by Clark in [Clark, 1997, Clark, 2008]. Further detail is provided by Wheeler [Wheeler, 2011] who contrasts the "Embodied cognition" and "Extended mind" notions and illustrates some of the concepts on the robotic experiments of Pfeifer and Scheier [Pfeifer and Scheier, 1997].

1.4 Synthetic methodology

The methodology adopted in this work is a synthetic one [Pfeifer and Scheier, 2001]. That is, we build and then study the behavior of artifacts. As can be seen in Fig. 1.1, the area spanned by synthetic sciences can be futher subdivided into (1) the intersection with empirical sciences – synthetic modeling, (2) the middle area concerned with general principles, (3) the intersection with the application domain.

In this work, we are concerned with cognitive phenomena. That is, we need to synthesize scenarios, in which the engagement of the agent with the environment can be described as cognitive. This has guided the choice of the platform as well as the different tasks the robot is confronted with. We will analyze these choices in the closing section of this chapter (section 1.9). The behavior as well as internal workings of the robots will be analyzed and—to further facilitate the understanding of the phenomena under inspection—the conditions will be systematically modified. In a nutshell, the case studies presented are concerned with the structure of the sensorimotor space: how it is shaped by an agent's body and dynamic interaction with the environment and

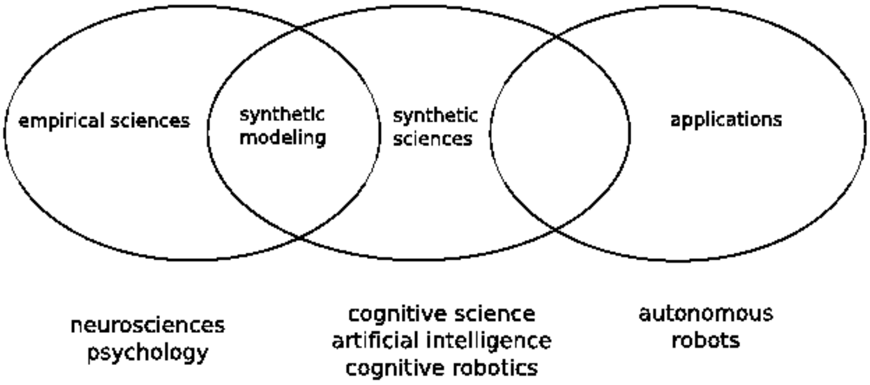

Figure 1.1: Overview of approaches to the study of cognition. The figure and caption are adapted from [Pfeifer and Scheier, 2001] to the study of cognition rather than intelligence. On the left, we have the empirical sciences like neurosciences and psychology that mostly follow an analytic approach. In the center, we have the synthetic ones, namely cognitive science, AI, and cognitive robotics which can either model natural agents (this is called synthetic modeling—the intersection with empirical sciences) or alternatively can simply explore issues in the study of cognition without necessarily being concerned about natural systems. From this activity, industrial applications can be developed, such as autonomous robots.

how invariant relationships can be extracted and exploited by the agent to improve its behavior. We may thus say that the general principles and mechanisms of the foundations cognition are being investigated—corresponding to the middle region in Fig. 1.1.[5]

Do the case studies presented in this dissertation qualify as synthetic modeling, i.e. as models of biological cognition too? Given that we do not treat cognition as an exclusively biological phenomenon, this possibility is open. We will be drawing from theories of biological cognition and instantiating, exploring and testing them in robots. However, the parallel between biological cognitive agents and the artificial ones will remain on an abstract level. We will not directly relate to any empirical data from the animal kingdom.

The last feature of the synthetic sciences is the overlap with the application domain. The case studies presented in this thesis carry substantial application potential with respect to increasing the robots' autonomy. This will be further detailed in the text.

A diagram similar to Fig. 1.1 locating all the case studies with respect to the methodology used will be presented in Chapter 2, Fig. 2.3.

1.5 Development and developmental robotics

The enactive view, but not only this view, emphasizes the effect of development on cognition. Development has been appreciated by the connectionists [Elman et al., 1996] as well as by researchers that emphasize embodiment and dynamic, reciprocal interaction with the environment (e.g., [Piaget, 1953, Goldfield, 1995, Thelen and Smith, 1994]). Let us very briefly look at the development of cognition in infants. Then, we will introduce the cognitive developmental robotics field, which follows the synthetic methodology.

[5]This could be also labeled the "animat approach". Cf. [Webb, 2009] and the responses in [Di Paolo, 2009] for a critical review. Our own account in defense of the animat approach can be found in [Hoffmann and Pfeifer, 2009] and [Hoffmann, 2010].

1.5.1 Infant development

To review cognitive development in infants is beyond the scope of this work. The interested reader is referred to the abundant literature. A treatment specifically targeted for deployment in robotics is provided by [Lungarella et al., 2004, Vernon et al., 2010b].

In particular, for the purposes of the studies performed in this work, it is mainly early postnatal development—from about 5 to 10 months of age—that is relevant. During this time, the infant explores the world actively and learns about her own body first. We have reviewed work on how infants acquire a sense of body ownership and agency in [Hoffmann et al., 2010] – Appendix B, section II. C. In a next stage, the infant learns about the relationships of objects, actions and effects. The learning proceeds first in a goal-free fashion, through self-exploration and self-observation. Later, from approximately 9 months of age, the learned relationships are exploited in goal-directed ways, anticipating a desirable change in the environment and behaving accordingly (see [Ugur et al., 2011] and the references contained therein). In general, it is pre-linguistic knowledge that is being acquired at this stage.

1.5.2 Cognitive developmental robotics

The core of the work undertaken in the context of this dissertation would fall under the label ”Cognitive developmental robotics“.

> Cognitive developmental robotics (CDR) aims to provide new understanding of how human higher cognitive functions develop by means of a synthetic approach that developmentally constructs cognitive functions. The core idea of CDR is ”physical embodiment“ that enables information structuring through interactions with the environment, including other agents. The idea is based on the hypothesized developmental model of human cognitive functions from body representation to social behavior. [Asada et al., 2009]

CDR is thus a subset of developmental robotics in general, which has the same mission, but is not concerned with cognitive phenomena only (however, we have to keep in mind that the boundary between sensorimotor and cognitive phenomena is blurred). For instance, the topics may include early motor development, prenatal [Kuniyoshi and Sangawa, 2006], or postnatal [Berthouze and Goldfield, 2008]. A review of developmental robotics is provided by Lungarella et al. [Lungarella et al., 2004] or by a special issue of the Infant and Child Development Journal [Prince, 2008]. A review of CDR is provided by Asada et al. [Asada et al., 2009].

First, as described above, CDR considers physical embodiment and information structuring through interactions with environment as a foundation for further cognitive development. We have reviewed a number of case studies that illustrate the physical as well as informational effects of embodiment in [Hoffmann and Pfeifer, 2011]. The publication is attached in Appendix A. Second, ”body representation“ seems to be the next key ingredient on the path to cognition. To this end, we have compiled an extensive review [Hoffmann et al., 2010], which is enclosed as Appendix B. In particular, the work in robotics that is oriented at modeling biological phenomena is presented in the Section IV ”Robots as models of biological body representations“.

As a representative example of the work in cognitive developmental robotics, the iCub humanoid robot needs to be mentioned. This is an open platform for research in embodied cognition (e.g., [Metta et al., 2010]), in which all facets of cognitive development are investigated and integrated. The book by Vernon et al. [Vernon et al., 2010b] provides an overview of the iCub cognitive architecture as well as a survey of other cognitive architectures.

1.6 Minimal cognition from bottom-up

Thus far, we have pointed out the problems of cognitivism (section 1.1) and argued in favor of the embodied approaches to cognition (section 1.3). However, the debate has been largely abstract and evidence in favor of the respective paradigms or theories was often indirect. Consequently, it is not easy to imagine minimal working examples that could be transferred to a robot and serve as a testbed for individual viewpoints. The behavior-based robotics paradigm (section 1.2), on the other hand, provided very concrete scenarios, in which the mechanisms responsible for generating the behaviors could be analyzed. Yet, these agents were typically restricted to reactive behaviors and could not learn from experience to improve their behavior over time. Therefore, they could hardly be considered cognitive. The goal of this work is to bridge this gap. To this end, we are interested in instances of minimal informational structures that the agent can autonomously acquire through the interaction with the environment and later exploit to act more effectively.

We will proceed as follows. First, we will point out the effect of embodiment on the informational processes that enter the agent's brain. Then, we will look at two concepts that qualify as the first steps on a cognitive ladder or "minimal representations" [Clark and Grush, 1999]: body schema and forward internal models. Finally, we will discuss sensorimotor-contingencies, which will serve the same function for us, but to what extent they should be called representations will require further discussion.

1.6.1 Impact of embodiment on informational processes

The effects of embodiment manifest themselves not only directly in the physical world, but have a profound influence on the information flows that enter the brain/controller of an agent. These effects can be quantified using information theoretic methods (e.g., [Lungarella and Sporns, 2006]). We have reviewed a number of case studies that illustrate this effect in [Hoffmann and Pfeifer, 2011]. The publication is attached in Appendix A; please refer to the sections "Information theoretic implications of embodiment in locomotion", "Information theoretic implications of embodiment in grasping", and the "Visual perception case studies".

1.6.2 Body schema

As we have argued, the body has a critical influence on behavior as well as on the structure of informational processes that enter an agent's brain. Therefore, it may be beneficial for the agent to learn about the properties of its body and to store (or represent) them in one way or other. In fact, this step should probably precede learning about the world (in accordance with the findings on infant development, section 1.5.1), since the interaction with any outside objects will be mediated by the morphology of the body and the sensory apparatus.

Body schema and *body image* are widely used notions (e.g., [De Preester and Knockaert, 2005, Graziano and Botvinick, 2002, Haggard and Wolpert, 2005, Holmes and Spence, 2004, Maravita et al., 2003]). Body schema is usually referring to a representation of the body for action, whereas body image is usually concerned with perceptual or spatial representation of the body. However, this so-called *dyadic taxonomy* may be too restrictive (see [de Vignemont, 2010]) and in biological reality, there is probably a multitude of overlapping and interacting representations. We have provided a review of the different notions as well as of empirical evidence that supports them in [Hoffmann et al., 2010]. This publication is attached in Appendix B. Please refer to the section "Body representations in biology". For the purposes of this dissertation, we will focus more on body schema than body image. A working definition is provided below.

Definition 1. *The body schema is a sensorimotor representation of the agent's body that is used to guide actions.*

Yet, this definition is still far from an operational definition that could lead to a direct implementation in an artificial agent. [Graziano and Botvinick, 2002] provide more "flesh" to the meaning of a body schema:

> ... we use the term broadly to mean an implicit knowledge structure that encodes the body's form, the constraints on how the body's parts can be configured, and the consequences of this configuration on touch, vision, and movement. The body schema plays a central role in interrelating concurrent perceptual inputs, allowing for the reconstruction of missing information, enabling the detection and resolution of conflicts, and ensuring an integrated, globally consistent multimodal representation of the body's configuration.

The counterpart of a body schema in robotics and control theory is a model of the robot (also model of the plant) that is used for control. However, such a model is typically defined from the outside and encompasses only specific explicit mappings, such as forward or inverse kinematics (cf. [Hoffmann et al., 2010], Appendix B, section III. B for details). Instead, we are seeking ways how the robots could autonomously—without relying on an engineer measuring the robot's body for instance—acquire and utilize models of their bodies in a bottom-up fashion. We have reviewed work in robotics in this direction in Appendix B, section III. D. In section IV., robots serving the goal of modeling biological body representations are reviewed.

In this work, we will adopt a truly bottom-up approach and investigate, from an agent's situated perspective, which patterns in the sensorimotor flows can be attributed to its body and how they can be exploited by the agent. This will mainly be the topic of Chapter 4 and Appendix D.

1.6.3 Forward internal models

Another "building block" that can be useful for a minimally cognitive agent is a *forward model*. Unlike body schema, forward model is very easy to define, probably thanks to its origins in control theory.

Definition 2. *A forward model is a mechanism that predicts the future state of a system, given the current state and a control signal.*

Unlike in a body schema, there is an explicit time dimension (current state, future state). A comparison of (short- and long-term) body schema, forward and inverse models and peripersonal space representation is provided in section II. E of Appendix B. As we have argued in section 1.3.1, forward models can be considered the simplest instances of emulator circuitry, which can later provide the basis for "off-line reasoning"—a hallmark of cognition for many [Clark and Grush, 1999, Grush, 2004, Barsalou, 2008].

Forward model was picked up by researchers in vertebrate motor control and has become a crucial explanatory concept. It is realized like this: the inputs are current sensory state and a motor command copy ("efference copy"), the output is the future (predicted) sensory state ("corollary discharge"). Such a model can be trained by simply executing the actions in the real world and using the sensory stimulation from the real world to train the predictor. In this form, it can already be used to (i) predict the next sensory state in advance; (ii) distinguish self-generated sensory information from sensory input generated by the environment. The first point can be useful during rapid locomotion, for instance, since biological feedback comes with considerable delay. The second point can facilitate effective detection of changes in the environment. There is substantial evidence supporting the existence of such circuitry in insects (e.g., [Webb, 2004]) as well as mammals [Wolpert et al., 1998, Kawato, 1999, Franklin and Wolpert, 2011], where the mechanisms start gaining in complexity: inverse models and even multiple paired forward and inverse models are hypothesized. However, the existence of these mechanisms is still disputed, in particular by the proponents of the equilibrium-point hypothesis (e.g., [Ostry and Feldman, 2003, Feldman, 2009, Feldman, 2011]).

In this work, we will implement and analyze the workings and utility of architectures that encompass forward and inverse models. All of the case studies touch on this topic, but it is specifically addressed in Chapter 6, App. F, and Chapter 7, App. G.

1.6.4 Sensorimotor contingencies

The Sensorimotor Contingency Theory (SMCT) was proposed by O'Regan and Noe [O'Regan and Noe, 2001] to explain perceptual experience, focusing on vision and visual consciousness in particular.

> Instead of assuming that vision consists in the creation of an internal representation of the outside world whose activation somehow generates visual experience, we propose to treat vision as an *exploratory activity*. We then examine what this activity actually consists in. The central idea of our new approach is that *vision is a mode of exploration of the world that is mediated by knowledge of what we call sensorimotor contingencies*. [O'Regan and Noe, 2001]

This view is strikingly similar to the account of seeing provided by the American pragmatic philosopher John Dewey already in 1896.

> Upon analysis, we find that we begin not with a sensory stimulus, but with a sensory-motor coordination [...] In a certain sense it is the movement which is primary, and the sensation which is secondary, the movement of the body, head, and eye muscles determining the quality of what is experienced. In other words, the real beginning is with the act of seeing; it is looking, and not a sensation of light. [Dewey, 1896]

Very similar accounts have been put forward by other authors, for instance the French phenomenologist Maurice Merleau-Ponty (e.g., [Merleau-Ponty, 1962]). This has been recently labeled as a "pragmatic turn" in cognitive sciences by Engel [Engel, 2011]: "away from the traditional representation-centered framework toward a paradigm that focuses on understanding the intimate relation between cognition and action."

Sensorimotor contingencies can be defined as follows [O'Regan and Noe, 2001]:

Definition 3. *Sensorimotor contingencies correspond to the structure of the rules governing sensory changes produced by various motor actions.*

Different modalities—vision, audition, or touch—would be associated with different sensorimotor contingencies and this is what makes seeing different from hearing or touching. These are called modality- or apparatus-related SMCs. O'Regan and Noe [O'Regan and Noe, 2001] review empirical evidence from psychology and neuroscience to support this view of perception. Additional evidence is provided by [Engel, 2011].

How does SMCT help us on the road to minimal cognition? Compared to forward models, neither the implementation nor the interpretation is straightforward. Regarding the implementation, SMCT is not articulated concretely enough to be used as a ″building block“ in a cognitive agent. The definition is more concrete than in the case of a body schema; yet, it leaves room for interpretation. In addition, what do the notions ″knowledge“, ″mastery“ and ″exercising“ of sensorimotor contingencies (SMCs) that are used in [O'Regan and Noe, 2001] exactly stand for? Therefore, in this work, we will address the issues of extracting, storing, and using SMCs in concrete scenarios.

On the conceptual level, why would we want to call an agent using SMCs cognitive? First, [O'Regan and Noe, 2001] propose ways how SMCT can address not only very low level perception (or sensation), but also object perception. Perceptual categorization (cf. also section Embodied categorization in Appendix A) can be achieved through longer sensorimotor sequences. Whereas the modality-related SMCs will be dominant on a shorter time scale, longer interaction sequences with a particular object will allow the object to leave a ″unique footprint“, which will give rise to object-related SMCs. Second, although predictive mechanisms are not explicitly elaborated by SMCT, they seem to be implied by the very notion of SMCs as lawful changes in sensory stimulation that result from the agent's actions. Thus, anticipatory capabilities—another cognitive hallmark—can be achieved with SMCs. In fact, the extension of SMCs to cognition is the theme of the eSMCs project (FP7-ICT-270212, `esmcs.eu`).

With regard to representations, the position of SMCT is ambiguous. Although the theory argues against representation, the knowledge of SMCs suggests that these need to be stored somewhere. Hence, it seems that it is mainly detailed, pictorial representations—″mirrors of the world states“ —that SMCT is arguing against.

In this work, we will provide a detailed analysis of the structure of sensorimotor space in a quadruped robot interacting with different environments in Chapter 4 and App. D. In Chapter 6 and App. F we will deploy a computational model of SMCs [Maye and Engel, 2011]. There, not only extraction, but also storage and exploitation of SMCs for action selection will be demonstrated.

1.7 Safe robots with long-term autonomy

As we have explained in section 1.4, investigating the mechanisms of cognition and modeling biological instances thereof is not the whole synthetic methodology: useful artifacts can be also developed in the process. In our case, these artifacts are autonomous robots. In fact, the perspective can be also turned around. Rather than obtaining applications as a ″side-effect“ of modeling efforts, cognitive traits should emerge from the needs that the environment is imposing on the agent. A similar scenario was proposed to explain the origins of (″offline“) cognition in nature ([Clark and Grush, 1999], section 1.3.1). In this work, we will adopt a similar strategy: we will manipulate the task/environment such that the agent cannot succeed if it relies on simple reactive behaviors only. At the same time, these scenarios constitute cases that have relevance for robotic applications.

1.7.1 The limitations of the robots of today

The way most robotic systems of today work is largely in accordance with the GOFAI framework outlined in section 1.1. The majority of robots operate in controlled, i.e. semi-virtual environments, facilitating the interface with their internal models that were designed by their creators. The fundamental problems (symbol-grounding problem, frame problem) were thus not resolved but circumvented: the engineers provide the meaning to the symbols (i.e. the symbolic representation is not meaningful to the system itself, but only to the designers of the system) and they also define the variables that need to be tracked and updated to keep them in tune with the real world state.

Concretely, industrial robots and the models have some typical characteristics: (i) the robots are stiff and equipped with high-speed, high-power actuators; (ii) the interaction with the environment is largely predefined, (iii) the models are fixed, explicit and centralized. These characteristics are well suited for typical industrial settings, i.e. controlled environments. As a consequence, industrial robots often operate in cages to prevent unpredictable contacts with people. However, for the robots to expand their "ecological niche" several steps are necessary. First, their autonomy needs to be increased in order to be able to cope with unforeseen situations. Second, they need to be made safer.

1.7.2 Autonomous long-term operation in novel environments

Robots are starting to gradually broaden their task domains and operate in less and less controlled environments. Good examples are autonomous vehicles of the DARPA Grand Challenge (e.g., [Thrun et al., 2006]) or the Mars Exploration Rovers [Washington et al., 1999]. The control architectures in operation are essentially compatible with traditional GOFAI approaches. The information from arrays of very powerful sensors (laser range finders, cameras, radar) is mapped onto a 2D allocentric[6] representation of the world (an occupancy grid) in which a collision free path is planned. However, perception of the environment and classification into traversable vs. non-traversable terrain still remains a challenge, often relying on a supervised training phase with a set of labeled terrain examples [Bagnell et al., 2010].

Altough there has been remarkable progress, the community has recognized that more adaptivity and flexibility is needed if the machines are to independently operate on time scales ranging from days to years. This is testified by the DARPA LAGR Project (Learning Applied to Ground Robots, e.g. [Jackel et al., 2006]) and by the regular workshops organized at major robotic conferences as summarized by [Kelly et al., 2012].[7]

1.7.3 Safety through soft robotics

In order to enter environments with human presence, the robots need to made safe. One solution toward this goal is to make the robots "softer". This can be achieved by using compliant joints and elastic materials, for instance (cf. [Albu-Schaffer et al., 2008] for a review of engineering and [Trivedi et al., 2008] for bio-inspired solutions in soft robotics). Furthermore, the new mechanical properties can also take over part of the control problem (we have reviewed some case studies in this flavor in [Hoffmann et al., 2011a], Appendix A). However, new solutions to the control problem need to be devised. "Soft" robot bodies are very difficult to model analytically. Therefore, it is desirable that robots can develop, calibrate and adapt their models automatically, relying on their own sensory information. In addition, the robots should learn to exploit the interaction of their complex bodies with the environment rather than enforcing control over them.

[6] Also called exo- or geocentric. Linked to an external reference frame, as opposed to egocentric.

[7] There were Long-Term Autonomy workshops organized at ICRA 2011 and 2012, and Autonomous Long-Term Operation in Novel Environments workshops at RSS 2011 and 2012.

1.7.4 Paving the way toward applications in this thesis

This work is centered around a dynamic, compliant, underactuated quadruped robot. This platform is hard to control and model analytically and can thus be considered a "soft" robot. In this thesis, we will first deal with control: how can the robot learn different gaits (Chapter 3 and Appendix C). Then, we will address the problem of self-modeling: we will investigate the limits of how much can the robot learn about its body and interaction with the environment using on-board sensors only (Ch. 4 and App. D). We also suggest ways in which this information can be used for environment detection or self-diagnosis. Chapter 5 & App. E are concerned with path integration (dead reckoning), which is an important component of the navigation system of an autonomous vehicle. We develop a novel architecture that combines the information from the proprioceptive and pressure sensors on the robot's legs (a legged odometer) and inertial measurements. Chapter 6 and App. F address terrain discrimination and adaptive walking in the quadruped robot. No model of the robot or the environment is provided from the outside. Learning proceeds incrementally, employs redundant sensory information, and could be directly deployed in a long-term adaptation scenario. Finally, Chapter 7 and App. G address planning further into the future. In addition, the robot applies the same modeling method to learn about the consequences of its actions and to predict the behavior of another agent in the environment. The model is probabilistic, learned *ab initio*, and developed incrementally.

In summary, the topics addressed largely overlap with the themes that were put forth as challenges by the "long-term autonomy community" [Kelly et al., 2012]: resource-constrained long-horizon planning; long-term learning and adaptation; estimation in dynamic environments; fault tolerance and failure prediction; and online calibration.[8]

1.8 The approach to cognition in this thesis

Which cognitive science paradigm shall we adopt for this thesis and which definition of cognition? Our view is in line with the embodied cognition viewpoint in general (section 1.3). In particular, we are specifically concerned with minimal instances of cognition (section 1.6): under what circumstances and how do they come about in biological or artificial agents. In a nutshell, the case studies presented are concerned with the structure of the sensorimotor space: how it is shaped by an agent's body and dynamic interaction with the environment and how invariant relationships can be extracted and exploited by the agent to improve its behavior.

In this thesis, it is not our goal to further deeply engage in a theoretical debate on cognition. What we will do is study complete, most of the time physical, agents interacting with their environments. Pursuing some goals, an agent can better achieve them by appropriately modulating the interaction, either by modifying its body or its control structures.[9] Whether the goals can be better achieved by adapting the body or the controller depends on the nature of the interaction and also on the means of manipulating the one or the other that the agent has at hand. In higher organisms as well as in robots, the brain/controller is typically more plastic and versatile and can thus more effectively change the interaction even on very short time scales. The interaction is shaped by some constraints given by all the interacting components, giving rise to some invariant structures. A "footprint" of this interaction is induced in the informational processes in the agent's control structure.[10] Sensorimotor contingencies, as described above, is one concept that encompasses these regularities. Remembering these contingencies can be useful to the agent

[8] RSS 2011 ALONE Workshop, `http://robotics.usc.edu/~alone2011/`

[9] We intuitively place a boundary between the environment, the body and the brain somewhere, even though no sharp boundaries may exist.

[10] We need to keep in mind, however, that the processes in the brain are shaped by the interaction with the environment, but, at the same time, they are co-generating that interaction.

and allow him to better select its future ways of engagement with the environment—guide its future actions. In some situations, it may bring advantage to the agent to further "elaborate" these contingencies, trying to extract invariants that may be specifically attributed to its body—giving rise to a body schema—or to enhance them with a time dimension, allowing for internal (covert, "mental") simulation of sensorimotor sequences (forward models, emulators). It is not our goal to argue whether these vehicles (or "neural vehicles" [Engel, 2011]) should be called (internal) representations—this word carries a lot of not only cognitivistic burden with it (cf. [Harvey, 2008] or [Webb, 2006] for a disambiguation). What is important for us is that these internal informational structures are neither sufficient for cognition (as cognition does not occur in the brain), nor should they attempt to mirror the outside world in the brain, yet they may be very useful in supporting a successful interaction of the agent with the environment. In this thesis, we will explore how effectively can these vehicles contribute to the agent's behavior and what form and level of detail they should have.

1.9 From locomotion to cognition

What is the right platform for investigating cognitive phenomena? Given that the diversity of phenomena that we may call cognitive is too large, there cannot be any general answer to this question. Nevertheless, based on the perspective on cognition we have chosen in this thesis (see previous section, 1.8), we can list some requirements that should be met. These are primarily a complex embodied interaction with the environment and a rich motor and sensory apparatus. The interaction of the agent with its surroundings induces regularities in its sensorimotor space which the agent can learn about and later capitalize on. The particular way in which these basic preconditions are instantiated will then shape the kind of "cognition" that the agent can develop.

1.9.1 From locomotion or from manipulation to cognition?

The main ways in which animals and humans physically engage with the world can be grossly divided into manipulation and locomotion activities. Some researchers in cognitive robotics hold the view that manipulation is central to human cognition [Metta et al., 2010, Ritter et al., 2007]. For example, a lot of research on body schema focuses on the representations of the hand and the space around it (cf. Appendix B, Part II. C).

Ritter et al. [Ritter et al., 2007] explain how first very low-level interaction patterns need to be developed and later

> ... hand-eye coordination, bimanual coordination, and goal-directed sequences of manual actions introduce even more global levels of integration and give rise to the question how interaction patterns formulated originally at the level of physics can become connected with more abstract perspectives of action semantics, goal-directedness, and intentionality. [Ritter et al., 2007]

Evidence in support of this view comes from evolutionary anthropology [Byrne, 2003], for instance.

However, evidence relating the development of cognitive skills to locomotor capabilities is equally abundant. For example, Vernon et al. [Vernon et al., 2010b, Chapter 3] review evidence regarding the development of posture and locomotion and how this drives the acquisition of predictive abilities. In fact, a stable posture has to precede coordinated manual actions. Therefore, anticipatory postural adjustments (e.g., [Barela et al., 1999]) may the first prospective capabilities that an infant needs to master. Later, humans and animals need to learn about the extent of their bodies with regard to locomotor actions. For example, they learn to predict whether an aperture can be passed without shoulder rotation [Warren and Whang, 1987] or to adjust the foot trajectory when stepping over an obstacle [Mohagheghi et al., 2004]. Control and estimation of step length are other examples where a body representation of some sort (knowledge about intrinsic dynamics of limb segment motion, relationships between gait parameters and body proportions) may be required [Yvanenko et al., 2011].

Furthermore, "manual cognition" has the additional constraint that it is basically restricted to humans and primates. "Locomotor cognition", on the other hand, can be found in much lower animals. For example, path integration was discovered in ants [Wittlinger et al., 2006]; prediction was demonstrated in motor preparation of prey-catching behavior of a jumping spider [Schomaker, 2004]; frogs were found to be able to predict whether an aperture could be passed [Collett, 1982]; finally, rats were found covertly comparing alternative paths in a T-maze, thus "planning in simulation" [Hesslow, 2002].

In summary, the two—manipulation and locomotion—are rather closely intertwined and complementary (cf. also [Higuchi et al., 2006]) and both have their merits regarding investigations into cognitive phenomena. However, since the most low-level forms of cognition are our focus in this work, locomotion may in fact be a more appropriate setting.

1.9.2 Cognition in the Puppy robot

An obvious implication of the embodied cognition stance is that the kind of cognition that will emerge will be highly dependent on the body of the agent, its sensorimotor apparatus and the environment it is interacting with. That is, if our goal was specifically human cognition, a humanoid robot—or perhaps even better a baby humanoid like iCub [Metta et al., 2010]—would the best option. The main platform in our work was the quadruped robot Puppy.[11] Below, we will look at the main characteristics of our platform, which we will later use to draw some implications that these properties have for cognitive development.

- **Underactuation.** The robot has eight degrees of freedom: four hip/shoulder joints are actuated with servomotors, four "knee" joints are passive compliant with springs attached in such a way that they act as nonlinear torsional springs at the joints. Since this system has fewer independent control actuators than degrees of freedom to be controlled, it is called an *underactuated system* [Fantoni and Rogelio, 2002].

- **Rich nonlinear dynamics.** The nonlinear springs at the knees together with the robot's feet that were covered with a material with asymmetrical friction properties (low friction during leg protraction, high during retraction) contribute to the overall rich nonlinear dynamics of the robot.

- **Multimodality.** The robot is equipped with 18 sensors from different modalities. The sensory set is dominated by proprioceptive modalities: angular joint position sensors at the active and passive joints, accelerometers and gyroscopes. In addition, there are pressure sensors on the feet.

The first two points have the following implications. First, the fact that the agent has only weak control authority over its complex body means that it cannot simply enforce desired trajectories. Instead, it has to learn how to perceive and then exploit its natural dynamics. To this end, a model of its body, the nature of the interaction with the environment, and the consequences of different actions will be useful. The control problem (with full controllability, a trajectory can be simply enforced) is thus transformed to a planning problem that tries to achieve an objective with

[11] Please refer to the "Information flows in S-M space" case study (App. D), for instance, for a description of the platform and the sensor suite employed.

the means at hand.[12] Second, in the Puppy robot, there are no separated physical "modules" (unlike the majority of robots where if one joint is kept stiff, the parts before and after this joint can be controlled largely independently). As the robot runs, through the interaction with the ground, the influence of one leg will spread to all the other legs, for instance. This will impact the cognitive processes of the agent: they should become more continuous with the processes in the environment (as discussed in section 1.3.2). A self-model that the robot will develop will thus necessarily contain not only geometrical, but also biomechanical properties of its body and interaction with the environment.

The multimodal sensory set together with the nonlinear, partly passive, dynamics of the body provide powerful means to extract information about the body itself and the environment. In addition, the absence of distal sensors (camera) forces the robot to use all the modalities by actively probing the environment, which is in accordance with the action-based view on perception and cognition that we have adopted.

In summary, a dynamic, compliant locomoting platform with a range of proprioceptive modalities provides a valuable tool for research in the development of cognition. Furthermore, as we have observed in [Hoffmann et al., 2010] (Appendix B), it complements the research in robotics and cognitive robotics, which is biased toward stiff manipulator arms observed by a camera.

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1.9.3 Roadmap

This thesis presents a collection of case studies in which the quadruped robot Puppy gradually "climbs up a cognitive ladder", going from locomotion to cognition. In Chapter 3 and Appendix C, the robot first learns to walk—acquires a repertoire of gaits (controlled in an open-loop fashion). Then, it learns the first reactive behavior: speed adaptation on a moving treadmill. In Chapter 4 and App. D, the sensorimotor space—the raw material for cognition—is analyzed in detail. In the following chapters, the robot is presented with scenarios that require integration of information over time and the emergence of first cognitive capabilities. The scenarios are: path integration (Ch. 5 and App. E), terrain discrimination and gait adaptation (Ch. 6 and App. F), and moving target seeking (Ch. 7 and App. G).

[12] I owe this perspective to Jonas Buchli.

Chapter 2

Thesis overview

The overarching motivation of the work presented in this thesis is to explore the mechanisms that allow an autonomous agent to successfully master tasks of certain complexity—tasks that may be labeled ″cognitive″. We have explained our view on cognition in section 1.8. Our approach is synthetic (cf. section 1.4): we will present robots with certain tasks or scenarios, endow them with some basic capabilities and study if they can successfully cope with the situations and what are the mechanisms responsible for this. Our approach is ″From locomotion to cognition″. This means, first, that it is bottom-up. We will start with the most low-level behaviors (learning to walk in an open-loop manner or adapting speed with a simple reactive controller) and then progressively present the robot with scenarios that force him to leave the ″here-and-now″ time scale and to enter the realm of minimally cognitive capabilities: in short, the agent should extract the regularities in its interaction with the environment and use them to improve its behavior. Second, our path is centered around locomotion. We have explained the implications of this choice compared to manipulation scenarios in section 1.9.1. The main merit is that several simple cognitive phenomena that are observed in lower animals (path integration, body size estimation, ″mental″ simulation) fall into or are first developed in the locomotion context and can be investigated in a mobile robot.

This chapter provides an overview and is structured as follows. First, we will very briefly outline the context and related work. Then, we will outline the dissertation essence: five case studies that investigate different instances of minimally cognitive settings. Afterwards, we will point out some key facets of cognition that are explored in the individual case studies: origin of sensorimotor regularities, ″cognitive building blocks″ on the side of the agent (sensorimotor contingencies, body schema, forward models), the role of different time scales, and the ″degree of cognition″ on a simplified cognitive landscape. Finally, we will provide an overview of the methodology and the platforms used in individual case studies.

2.1 Context and related work

The overall context of this work was provided in the Introduction. In addition, two publications provide extensive additional material:

- **The implications of embodiment for behavior and cognition: animal and robotic case studies.** This paper provides a review of case studies that demonstrate, first, the direct effects of physical interaction with the environment on behavior. Second, it surveys case studies that show how sensory information that reaches the brain or controller is shaped by the morphology and by the actions of the agent. Finally, a path to embodied cognition is

sketched.
Appendix: The complete paper can be found in Appendix A.
Publication: Hoffmann, M. and Pfeifer, R. (2011). *The Implications of Embodiment: Cognition and Communication*, chapter The implications of embodiment for behavior and cognition: animal and robotic case studies, pages 31-58. Exeter: Imprint Academic.

- **Body schema in robotics: a review.** This paper provides a comprehensive overview of the concept that we have identified as a building block on a bottom-up way to cognition: body schema. Body representations in biology are reviewed from a functional or computational perspective to set ground for a review of the concept of body schema in robotics. First, we examine application-oriented research: how a robot can improve its capabilities by being able to automatically synthesize, extend, or adapt a model of its body. Second, we summarize the research area in which robots are used as tools to verify hypotheses on the mechanisms underlying biological body representations.
Appendix: The complete paper can be found in Appendix B.
Publication: Hoffmann, M., Marques, H., Hernandez Arieta, A., Sumioka, H., Lungarella, M. & Pfeifer, R. (2010). Body schema in robotics: a review. *IEEE Trans. Auton. Mental Develop.* 2 (4): 304-324.

For additional context and related work that is specific to individual case studies, the reader is referred to the original publications, which will be also presented in the Appendices.

2.2 Dissertation essence

The essence of this dissertation is constituted by five robotic case studies. As we have already sketched in section 1.9.3, they form a kind of roadmap for cognitive development in a mobile robot. The individual case studies are briefly summarized below. For each of them, we provide a brief synopsis and a "short name" that we will further use in the text and in schematic visualizations. Then, a short chapter will be devoted to every case study, where the main points in the context of this dissertation will be summarized (Ch. 3 to Ch. 7). We will integrate our findings in a single discussion and conclusion (Ch. 8). All five case studies are complete scientific publications and they are enclosed in the Appendices (App. C to App. G).

The first study, "Walking & speed adaptation", provides the starting point. There, the quadruped robot learns a repertoire of gaits in the form of different settings for a Central Pattern Generator (CPG). These rhythmic patterns are executed in an open-loop fashion[1] and give rise to periodic oscillatory motion of the robot's legs. Then, the robot uses one of the gaits ("bounding") and on top of it, it learns to adapt speed based on a distance measurement. This is achieved through a simple stimulus-response mapping and is thus an example of a reactive behavior. The next case study, "Information flows in S-M space", has an analytical nature: the sensorimotor space of the robot is analyzed in detail using information theory. We have argued that the regularities in this space constitute the raw material for any cognitive processes. We systematically vary the motor commands and the environment and study how much could the robot infer about its body, the character of its sensory modalities, and the different environments. In the following three case studies, we present the robot with tasks in which it has to extract the sensorimotor regularities and deploy their knowledge in solving a particular task. In the "Path integration" study, the robot combines the information from multiple sensory modalities and extracts estimates of its ego-motion, which are then integrated over time. In the "Terrain discrimination" study, the robot learns about the interaction with different ground substrates, how this interaction is modulated

[1] The target motor positions are generated in an open-loop manner and sent to the servomotors. These, however, follow the prescribed trajectories using an internal closed-loop (PID) controller.

by the use of different gaits, and what effects it has on the perceived comfort of locomotion. Based on this knowledge, the robot optimizes its action selection. Finally, in the "Moving target seeking" study, a mobile robot needs to learn about the consequences (change in distance and heading) of applying different motor commands and use this to catch another mobile robot. The difficulty of the task is progressively increased and the mechanisms that are needed to successfully cope with the task (increasing levels of planning) are investigated. In addition, the agent learns a simple model of the behavior of the "prey" robot, thereby extending the space of its cognitive processes to other agents.

1. **Learning to walk and to adapt speed.**
   Short name: Walking & speed adaptation.
   The quadruped robot learns a repertoire of gaits in the form of different settings for a Central Pattern Generator (CPG). These rhythmic patterns are sent as target positions to the hip and shoulder servomotors and give rise to periodic oscillatory motion of the robot's legs. Thanks to the underactuated nature of the platform (only four motors to control) and a "soft" control policy (no trajectories for center of mass, for instance, are prescribed), learning proceeds very fast. The gait repertoire learned is used in the subsequent case studies. In addition, the robot learns its first reactive behavior: to adapt speed based on a distance measurement.
   Chapter: The article's main points in the context of this thesis are summarized in Chapter 3.
   Appendix: The complete paper can be found in Appendix C.
   Publication: Hoffmann, M., Schmidt, N., Nakajima, K., Iida, F. and Pfeifer, R. (2011). Perception, motor learning, and speed adaptation exploiting body dynamics: case studies in a quadruped robot. In *Proc. Int. Symposium on Adaptive Motion in Animals and Machines (AMAM)*.

2. **Exploring the sensorimotor space using information theory.**
   Short name: Information flows in S-M space.
   This work presents a detailed quantitative analysis of the sensorimotor flows in a quadruped robot using information theory. Starting from minimal prior knowledge, through systematic variation of control signals and environment, we show how the agent can discover the structure of its sensorimotor space, identify proprioceptive and exteroceptive sensory modalities, and acquire a primitive body schema.
   Chapter: The article's main points in the context of this thesis are summarized in Chapter 4.
   Appendix: The complete paper can be found in Appendix D.
   Publication: Schmidt, N., Hoffmann, M., Nakajima, K., and Pfeifer, R. (2012). Bootstrapping perception using information theory: Case studies in a quadruped robot running on different grounds. *Advances in Complex Systems J.* 15 (6).

3. **Path integration from multimodal proprioceptive sensory information.**
   Short name: Path integration.
   Using a multimodal data set generated by a quadruped robot running with two different gaits on different grounds, a full body state (position, velocity, and attitude) estimator that does not use any external reference was implemented. A novel data-driven architecture for legged odometry that relies solely on a combination of joint sensor signals and pressure sensors is presented.
   Chapter: The article's main points in the context of this thesis are summarized in Chapter 5.
   Appendix: The complete paper can be found in Appendix E.
   Publication: Reinstein, M. and Hoffmann, M. (2011). Dead reckoning in a dynamic quadruped robot: Inertial navigation system aided by a legged odometer. In *IEEE Int. Conf. Robotics and Automation (ICRA)*, Shanghai, China, pages 617–624.

4. **Using sensorimotor contingencies for terrain discrimination and adaptive walking behavior.**
   Short name: Terrain discrimination.
   We use a computational model of Sensorimotor Contingency Theory (SMCT) for controlling the behavior of a quadruped robot running on different terrains. The study demonstrates that: (i) Sensory-Motor Contingencies (SMC) provide better discrimination capabilities of environmental properties than conventional recognition from the sensory signals alone; (ii) discrimination is further improved by considering the action context on a longer time scale; (iii) the robot can utilize this knowledge to adapt its behavior for maximizing its stability.
   Chapter: The article's main points in the context of this thesis are summarized in Chapter 6.
   Appendix: The complete paper can be found in Appendix F.
   Publication: Hoffmann, M., Schmidt, N., Pfeifer, R., Engel, A.K., and Maye, A. (2012). Using sensorimotor contingencies for terrain discrimination and adaptive walking in the quadruped robot Puppy. In Ziemke, T., Balkenius, C., and Hallam, J., editors, *From animals to animats 12: Proc. Int. Conf. Simulation of Adaptive Behavior (SAB), Odense, Denmark*, Vol. 7246 of LNAI, Springer, pages 54-64.

5. **Moving target seeking with forward and inverse models.**
   Short name: Moving target seeking.
   A simulated mobile robot was engaged in a predator-prey scenario. After an exploration phase, the robot automatically synthesized a forward model in terms of the change in distance and heading under each gait. However, in order to catch the prey robot, two additional components were needed: an inverse model and a prey model. All the models were learned ab initio, with minimal assumptions, they work in egocentric coordinates, and are probabilistic in nature.
   Chapter: The article's main points in the context of this thesis are summarized in Chapter 7.
   Appendix: The complete paper can be found in Appendix G.
   Publication: Oses, N., Hoffmann, M. and Koene, R. A. (2010). Embodied moving-target seeking with prediction and planning. In Corchado, E., Romay, M. and Savio, A., editors, *Proc. Hybrid Artificial Intelligence Systems (HAIS), San Sebastian, Spain, Part II*, Vol. 6077/2010 of LNCS, Springer, pages 478–485.

2.3 The facets of minimal cognition

In our explorations into minimally cognitive phenomena, we are primarily concerned with regularities that arise in the sensorimotor space and how the agents can learn about them, store them and use them to improve their behavior. To further structure this endeavor, we will first explain how our case studies specifically address the origin of these contingencies—in the brain, body, or environment. Second, we will provide an overview of the instantiation of cognitive "building blocks"—concepts that are hypothesized to underlie the basis of cognition (see section 1.6)—in our case studies. Third, we provide an overview of the time horizon involved in the respective scenarios. Finally, we will sketch a "cognitive landscape" and locate our case studies on it, in relation to some related work.

2.3.1 Tracing the origin of contingencies: brain, body or environment?

As we have already extensively argued, behavior is the outcome of the dynamic and reciprocal interplay of the brain, body and environment. This interplay is subject to some constraints which give rise to regularities or repeating patterns. These are then reflected in an agent's sensorimotor space and can be picked up by the agent. A natural way of making inroads into these ”footprints“ is through manipulation of the individual components that are co-responsible for the underlying behavior (please consult Appendix D: section 2.2.3 and Fig. 3). Manipulating the "brain" seems to be the easiest in artificial systems and we have studied that in all our case studies. Concretely, as we were dealing with legged robots, we have varied the periodic control signals sent to the robots' actuators that resulted in distinct gaits (somewhat resembling the gaits exhibited by animals—like walking, bounding etc.)[2]. In addition, in the first three case studies, we have also manipulated the environment by changing the ground types on which the robot was running. Using the data sets obtained, we have analyzed:

- **The effect of different control signals.** We have used distinct coordinated periodic control signals that gave rise to dynamic regimes in the robot: different gaits. These distinct regimes give also rise to unique "footprints" in the sensorimotor space. We have analyzed this in detail in the "Information flows in S-M space" case study (Ch. 4 and App. D). In the "Terrain discrimination" case study (Ch. 6 and App. F), we contrast the effect of the gaits with the effects of different grounds on the sensory space and show that environment discrimination can be substantially improved if the control signal is explicitly taken into account. Finally, the "Path integration" (Ch. 5 and App. E) and "Moving target seeking" (Ch. 7 and App. G) case studies are also concerned with the effect of different control signals; however, there, it is not (the structure of) the whole sensorimotor space that is investigated, but only its subset: concretely the relationship with the distance and direction travelled by the robot.

- **The invariance due to the body.** The body was not varied in our experiments. However, as the other main components—the control signals and the environment—were systematically manipulated, it was to some extent possible to investigate its effect by uncovering the invariant (always present) structure in the sensorimotor space. This is shown in the "Information flows in S-M space" case study.

- **The effect of different environments.** We have studied the changes to as well as invariants in the structure of the sensorimotor space as induced by different environments in the "Information flows in S-M space" case study. Unlike the changes of control signals, environmental changes are not directly accessible to an autonomous agent[3]: it is something that the agent needs to detect. Therefore, in the "Information flows in S-M space" and "Terrain discrimination" case studies, we have investigated how the robot could discriminate different environments based on changes in the sensorimotor patterns. In the "Path integration" case study, we have used a complementary approach: searching for a multimodal odometer, we were looking for invariants in the sensorimotor space that hold across different environments.

2.3.2 Cognitive building blocks

For sensorimotor spaces of certain size, it is not possible to discover and record all the regularities that the agent experiences. Different subspaces may be particularly relevant for the agent. The "cognitive building blocks" that we have reviewed in section 1.6 essentially correspond to such "subspaces". In this section we will provide an overview of their instantiation in our case studies.

[2] Please note that the gait and the control signal are not identical. The control signal is only co-responsible for the gait that the robot exhibits. The gait is a behavior, the control signal its "neural vehicle".

[3] In biological agents, the situation may be more complicated. All the details of low-level motor commands may not be "accessible" to higher-level circuitry. Thus, detailed control signals may not be available to higher cognitive processes as well.

Body schema

The body schema is defined as the sensorimotor representation of the agent's body that is used to guide actions. However, all the patterns in the sensorimotor domain are mediated by the agent's body (which includes the morphology of the sensory apparatus). The boundary between the body and the environment may also not be sharp, which is even more prominent in our platform (cf. section 1.9.2). Therefore, which subspace would correspond to the body schema? In the "Information flows in S-M space" study, we investigate two possibilities. First, we study the structure of the sensorimotor space that is invariant to changes in the motor commands and the environment. Second, we study which sensory channels are strongly affected by the motor signals. This provides an alternative view: the agent's body is what it can control. In the other case studies, we do not attempt to specifically extract a body schema. Instead, we are interested in specific task-relevant mappings in the sensorimotor space, which are, nevertheless, necessarily shaped by the body properties.

Forward models

Forward models in the context of sensorimotor space are functions that map a sensory state and a motor command to a future sensory state ($f(s_t, a_t) \rightarrow s_{t+1}$). Compared to body schema, we can note that, first, the definition is clear and concrete and can be directly implemented. Second, there is an explicit time dimension (states of the sensory or motor space at different moments in time). We have directly implemented a forward model in the "Moving target seeking" case study as a mapping from the current position and orientation of the robot to the next position or orientation under application of a given motor command. The robot acquires this model after randomly trying out different actions. A simple Bayesian network is used to store the learned relationships. An inverse model is obtained through Bayesian inference. Finally, the forward model is iterated internally and used for multi-step planning, corresponding to the concept of a decoupled forward model—an instance of "offline reasoning" [Clark and Grush, 1999], as explained in section 1.3.1. In the "Terrain discrimination" study, we use a similar, yet slightly different, mapping. The robot records previously experienced sequences of sensory-motor states. Using this knowledge, it can predict the next sensory-motor pair ($f(s_t, a_t) \rightarrow (s_{t+1}, a_{t+1})$). Considering only a particular next action (which is under the robot's control), the robot can predict its consequences, obtaining a mapping of the form $f(s_t, a_t, a_{t+1}) \rightarrow s_{t+1}$. This a variant of the forward model which highlights the importance of action for the sensory stimulation in the same time interval. Again, we have used a probabilistic representation of the model. In this case study, only one time-step lookahead was used. However, the architecture can be extended to plan further into the future.

Sensorimotor contingencies

Finally, let us analyze the sensorimotor contingencies (SMCs). In general, all the case studies deal with extracting regularities in the sensorimotor space and using them to improve the robot's behavior. Thus, loosely speaking, they are all concerned with SMCs. However, not all of them satisfy the notion of SMCs as we have defined it (according to [O'Regan and Noe, 2001]) in section 1.6.4: structure of the rules governing sensory changes produced by various motor actions. In the "Information flows in S-M space" study we are trying to uncover this structure using information theory. However, our interest is broader: we analyze the information structure among sensory modalities as well (i.e., not only structure of the motor-to-sensor information flows). In the "Path integration" study, we focus on the relationship between sensory variables and an external variable: the robot's stride length. These relationships are conditioned on the robot's action—different gaits require different odometers, since the mappings change with the gaits. This would thus be an SMC only in a very broad sense. The "Terrain discrimination" case study addresses SMCs explicitly by employing a discrete computational model of SMCs [Maye and Engel, 2011]. Finally, the “Moving target seeking” study is explicitly employing a forward model. Thus, it deals with SMCs to the extent that a forward model is a sensorimotor contingency. Again, we may say so in a broad sense.

2.3.3 The time axis

Behavior as well as cognition are a result of processes that involve different time scales. The same is true for the contingencies that are induced in the sensorimotor space. As we have discussed in sections 1.3.1, 1.6, and 1.8, remembering these contingencies can bring behavioral advantage for the agent: Past experience can be used to predict future courses of events. In this way, the agent can ”break the here-and-now-barrier“ of reactive stimulus-response behaviors [Vernon et al., 2010a] and cope with more complex tasks. Yet, what are the appropriate time scales and time horizons that the agent should consider? The advantage of the synthetic methodology is that the timing is largely under our control: it can be precisely measured and even manipulated. We have used different time steps in the robot controllers as well as different time spans: the time intervals for which the agents integrate information from the past and how far into the future they plan. This time horizon spanned by individual case studies is illustrated schematically in Fig. 2.1. The “Walking & speed adaptation” case study involves only the reactive, “here-and-now”, time scale and has therefore zero span on the schematics. In the “Information flows in S-M space” case study—where we performed a detailed information theoretic analysis of the sensorimotor flows—we concentrated on contingencies that are observable over a one second interval, corresponding to one period of the robot’s locomotion. The “Path integration” case study is specifically devoted to the past: the robot learns specific invariant relationships and then exploits past sensorimotor information in order to integrate the distance travelled. In the “Terrain discrimination” case study, we specifically demonstrate how the agent can use longer sensorimotor sequences to improve environment discrimination. At the same time, it employs the sensorimotor knowledge of the past to predict the future in order to choose the best action. The same strategy is used in the “Forward and inverse models” case study, but extended further into the future by iterating the forward model.

2.3.4 The cognitive landscape

In this section, we will strive to sketch a “cognitive landscape”, in which we will locate our case studies and some related work. As we have already analyzed, cognition is a very difficult phenomenon and any attempt to “pin it down” in a single diagram is bound to fail. Nevertheless, we believe that it will still be valuable for the reader to depict some of the key facets of cognition and their instantiation in our case studies in a graphical form. This attempt is shown in Fig. 2.2.

We have chosen two axes. The x-axis essentially follows the viewpoint of Barsalou [Barsalou, 2008], and Clark & Grush [Clark and Grush, 1999], who used the capability of offline reasoning (or “environmentally decoupled thought”) to demarcate cognitive agents (from non-cognitive agents). We have reviewed this viewpoint in section 1.3.1. Thus, on this axis, Passive Dynamic Walkers [McGeer, 1990] would lie on the very left, as they are completely coupled to their physical environment. Examples of behavior-based robotics (section 1.2) would also occupy the left side of the axis, which is reserved for reactive agents—creatures capable of simple stimulus-response behavior only. We have located the tortoises of Grey Walter [Walter, 1953] more to the left than the subsumption architecture [Brooks, 1986] because the tortoises were composed of direct, analog links connecting sensors and motors, whereas the subsumption architecture—composed of several interacting layers and containing internal states—is slightly more “decoupled” from immediate interaction with the environment. The distribution of our own case studies essentially

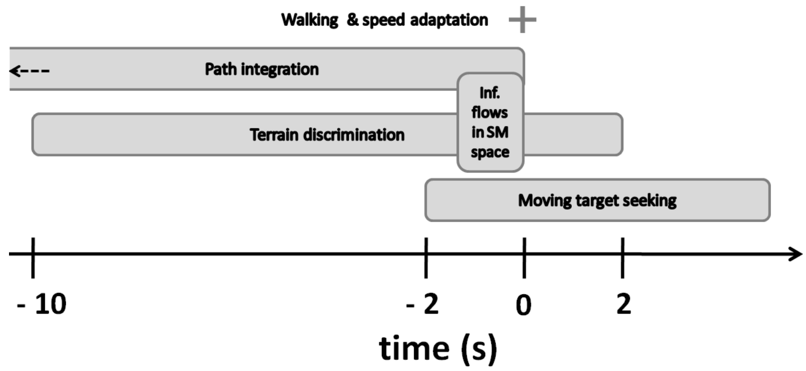

Figure 2.1: **Time horizon in individual case studies.** This figure illustrates the interval for which the agents integrate past sensorimotor information and how far into the future they plan. In the "Walking & speed adaptation" study, the agent is learning motor patterns in an open-loop fashion and then learns to adapt speed using a simple reflex. It thus exhibits reactive, "memory-less" behavior. The "Information flows in S-M space" case study is concerned with 1 second time intervals only (individual locomotion periods). The "Path integration" case study uses the same time interval for training a stride length estimator. However, consecutive estimates are then combined over much longer time intervals (e.g., 2 minutes). In the "Terrain discrimination" case study, a history of actions and respective sensory observations up to 10 seconds is used to detect the context. Based on that, the robot chooses the optimal gait for the next epoch (2 seconds into the future). In the "Moving target seeking" case study, short past sequences of gaits are used to learn their effect on the robot's change of position and heading, giving rise to a forward model. This is then used to plan future sequences of gaits.

directly follows from the previous section and Fig. 2.1. The "Walking & speed adaptation" study had zero span on the time axis, corresponding to "memory-less" behavior, from which a negligible offline reasoning capability follows. The other case studies[4] do integrate past sensorimotor information or project it into the future and thus move beyond the "here-and-now" time scales of reactive behavior. The "Terrain discrimination" study is in a sense most advanced, as it purposefully integrates past information to improve the behavior in the future. Further on the right are the mobile robots Stanley (DARPA Grand Challenge winner, [Thrun et al., 2006]) and Stanford Cart of Hans Moravec [Moravec, 1983]. The position of Cart further to the right is to mark that Cart was "decoupled" to the extent that it had lost real-time responsiveness (thinking around 30 minutes before every action). The chess computer, Deep Blue, is definitely capable of offline reasoning; yet it remains in contact with real time, as it has limited thinking time.

A disclaimer is in order: the axis is not to be interpreted in the way that "cognitive behavior" is a desired feat and being on the very right is the goal. First, the need for offline reasoning depends on the task. Second, the aim seems to be offline reasoning capability and real-time responsiveness at the same time. An additional axis would then be needed.

The second axis we have chosen depicts the nature of the internal informational structures that mediate the agent's interaction with the world. They were called "neural vehicles" by Engel [Engel, 2011], avoiding the problematic label of "representation". The axis spans the space from no internal vehicles over sensorimotor space to symbolic spaces. Obviously, there are no such structures in the Passive Dynamic Walker. In all case studies presented in this dissertation, the neural vehicles operate directly in the sensorimotor domain. The "Terrain discrimination" study uses all the modalities in a holistic fashion; the "Path integration" study, on the other hand, employs external reference frames and a carefully designed Kalman filter scheme, thus deserving a position further up this axis. Stanley, for example, deals with an internal world model in

[4] The "Information flows in S-M space" study is not shown, since it has an analytical rather than "behavioral" focus.

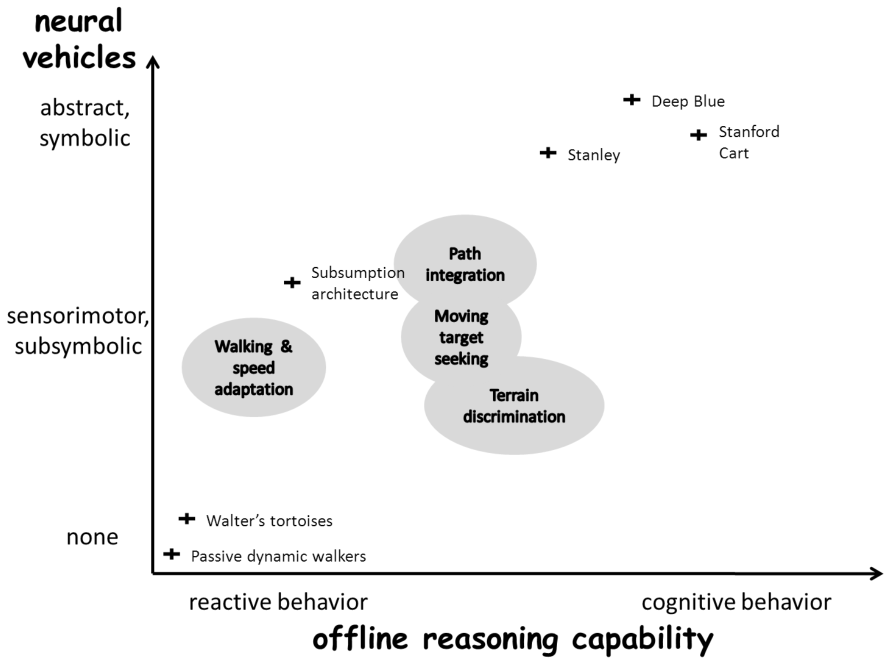

Figure 2.2: Cognitive landscape. This figure depicts the case studies and some related work on a didactic "cognitive landscape". See text for details.

the form of an occupancy grid, which is highly abstracted from its sensorimotor experience. A chess computer (Deep Blue) is confronted with an already symbolic, discrete world which is then simply replicated in its "brain".

This axis does not have a normative character either: the suitability of different neural vehicles depends on the task. However, the abstract/symbolic worlds—if designed from the outside rather than developed in a bottom-up fashion—are vulnerable to the symbol grounding problem [Harnad, 1990].

2.4 The methodological axis

First of all, as explained in section 1.4, the work presented in this dissertation encompasses several research goals and methodologies. Fig. 2.3 schematically locates each of the case studies on the "methodological axis". The core of our investigations is focused on understanding the general principles of minimally cognitive phenomena by exploring them in artifacts – robots. Therefore, all case studies occupy the middle region: synthetic sciences.

Furthermore, as we have explained in section 1.4, the investigations are targeting biological phenomena too. This can be on a level of cognitive mechanisms or on the task level. The former are addressed in particular in the "Information flows in S-M space" case study, in which we investigate how an agent can learn the structure of the outside world with minimal prior knowledge, and in the "Terrain discrimination" study, where we implement and test some of the premises of the Sensorimotor contingency theory (SMCT), a theory coming from empirical sciences. On the task level, some case studies specifically address problems that are solved by biological agents as well. This is in particular true for the "Walking & speed adaptation", "Path integration", and "Ter-

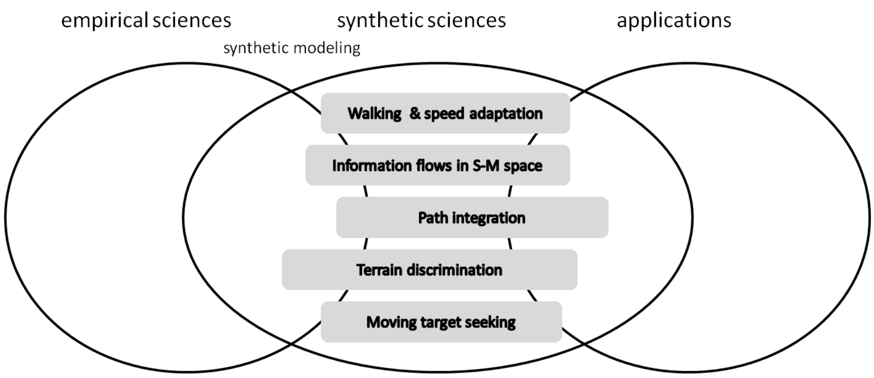

Figure 2.3: Case studies on a methodological landscape. The dominant methodology applied was a synthetic one: we have engaged embodied agents in different scenarios, studied their behavior, developed and manipulated their internal control structures and observed the effects. All of the case studies also enter the synthetic modeling region—that is they serve, or may serve after futher elaboration, as models of biological cognitive phenomena—as well as the region of applications. The "Path integration" case study is the most mature in this respect.

rain discrimination" studies. In section 8.3.3, we will further elaborate on how the case studies can be extended in the direction of modeling biological phenomena.

All of the case studies are also relevant for applications in autonomous robotics. We have outlined the major directions in section 1.7. They are mainly automatic model acquisition and autonomous navigation. The "Path integration" study is the most developed in this respect, as it introduces a novel framework for state estimation, which can be—after adaptations to a particular platform—deployed in legged robots. We will summarize the application relevance of every case study in the respective chapters and finally, we will recapitulate the contributions to robotics in section 8.2.2.

2.5 Platform

The case studies were centered around a quadruped robot Puppy. Please refer to the "Information flows in S-M space" case study (App. D, section 2.2), for instance, for a description of the platform and the sensor suite employed. The real robot was used in the "Walking & speed adaptation", "Information flows in S-M space", "Path integration", and "Terrain discrimination" case studies; in the last one, it was complemented by a simulated version of the robot. In the "Moving target seeking" case study, a simulated Khepera robot was used. This was a first study to prepare for a transition to the legged robot in a next stage. Therefore, the action repertoire of the wheeled robot was restricted to a small number of discrete "gaits" only.

We have already motivated the platform choice and explained the implications on modeling of cognition in section 1.9.2. In summary, the character of the animat used—a quadruped robot with rich body dynamics and a multimodal sensory set—is well suited as a tool for modeling embodied cognition. Unlike the Martian three-wheeled iguana that was provocatively put forth by Denett as an example of a possible cognitive creature [Dennett, 1978], our dog-like robot satisfies what Ziemke [Ziemke, 2003] has called "organismoid embodiment": an organism-like bodily form, with sensorimotor capacities akin to living bodies. In addition, it complements the research in robotics and cognitive robotics, which is biased toward stiff manipulator arms observed by a camera.

Chapter 3

Learning to walk and to adapt speed

This chapter refers to the publication [Hoffmann et al., 2011b] which is enclosed in Appendix C.

Hoffmann, M., Schmidt, N., Nakajima, K., Iida, F. and Pfeifer, R. (2011). Perception, motor learning, and speed adaptation exploiting body dynamics: case studies in a quadruped robot. In *Proc. Int. Symposium on Adaptive Motion in Animals and Machines (AMAM)*.

Below, we present the abstract and summarize the most important contributions with regard to the goals set in this thesis.

Abstract. *Animals and humans are constantly faced with a highly dimensional stream of incoming sensory information. At the same time, they have to command their highly complex and multidimensional bodies. Yet, they seamlessly cope with this situation and successfully perform various tasks. For autonomous robots, this poses a challenge: robots performing in the real world are often faced with the curse of dimensionality. In other words, the size of the sensory as well as motor spaces becomes too large for the robot to efficiently cope with them in real time. In this paper, we demonstrate how the curse of dimensionality can be tamed by exploiting the robot's morphology and interaction with the environment, or the robot's embodiment (see e.g., [Pfeifer et al., 2007]). We present three case studies with underactuated quadrupedal robots. In the first case study, we look at terrain detection. While running on different surfaces, the robot generates structured multimodal sensory information that can be used to detect different terrain types. In the second case study, we shift our attention to the motor space: the robot is learning different gaits. The online learning procedure capitalizes on the fact that the robot is underactuated and on a "soft" control policy. In the third case study, we move one level higher and demonstrate how - given an appropriate gait - a speed adaptation task can be greatly simplified and learned online.*

3.1 Minimally cognitive phenomena

This work briefly overviews three case studies: terrain detection, learning different gaits, and speed adaptation. We ask the reader to focus on the latter two (The first one, terrain detection, will be introduced in more detail in Ch. 6.). For the purposes of this thesis, learning to walk presents the most low-level task for our robot. We have used online optimization of an open-loop controller[1], which consists of sine waves of different parameters (amplitude, frequency, offset, phase lag) for the four motors in the robot's hip/shoulder joints. Interestingly, a diverse set of gaits (some of them akin to bounding or walking in animals, some tailored to the particular morphology of the Puppy robot) emerged. The controllers were evolved in a completely model-free fashion and can be taken as an example of "intelligence" without representation (cf. section 1.2): the behaviors are complex and to some extent even adaptive (rejecting perturbations thanks to mechanical feedback loops – self-stabilization [Blickhan et al., 2007]), but there are no internal informational structures in the system apart from a clock and a sinusoid generator. In the rest of the thesis, these gaits will constitute the basic motor repertoire of the robot.

In the "speed adaptation" case study, we closed the perception-action loop and studied a feedback control scenario.[2] The robot equipped with an ultrasonic distance sensor should keep a fixed distance from the end of a treadmill and respond to changes of speed of the running belt and to changes of target distance. The difficulty of the task largely depends on the complexity of speed modulation in the robot. We have developed a bounding gait in which the speed can be easily controlled with a single paramater: frequency of the sinusoidal trajectories sent to all legs. Moreover, the relationship between the frequency and the resulting speed of the robot was linear and the gait covered a big range of speeds. The task could then be accomplished with a simple proportional-derivative (PD) control of a single parameter: frequency. The controller was tuned by an online parameter search for the P and D gains. This case study is an example of a task that can be achieved with a reactive behavior: a simple mapping from the sensory signals to the motor signals. The interesting point in this case study is that the mapping responsible for the successful behavior was simplified by exploiting the low-level components—the gait the robot was running with.

In summary, we have included this case study to mark behaviors that we would not yet call cognitive. An agent blindly executing different motor programmes (gaits) or following direct mappings from the perceptual state to a motor pattern does not qualify as a cognitive agent. This is not to say that these behaviors are not important. On the contrary, they are ubiquitous and form the basic level of competence that every agent—animal or robot—needs to have. However, as we have argued, some degree of integration of information over time is required for the agent to leave the reactive domain. This will be the topic of the next chapters.

3.2 Toward applications

For autonomous robots, the dimensionality of sensory and motor spaces often poses a challenge. The common denominator of the case studies presented in this work was to illustrate how to tame the curse of dimensionality by exploiting the robot's morphology and the interaction with the environment. On the perceptual side, this is achieved by taking advantage of the prestructuring of sensory information as a result of active generation of sensory responses through the agent's body interacting with the environment. On the motor side, dimensionality is reduced by exploiting the underactuated nature of the robot and by applying a "soft" control scheme. However, this comes at the cost of versatility: only certain behavioral patterns are possible.

[1] The target motor positions are generated in an open-loop manner and sent to the servomotors. These, however, follow the prescribed trajectories using an internal closed-loop (PID) controller.

[2] This paragraph is adapted from [Hoffmann et al., 2011b], App. C.

Chapter 4

Exploring the sensorimotor space using information theory

This chapter refers to the publication [Schmidt et al., 2012] which is enclosed in Appendix D.

Schmidt, N., Hoffmann, M., Nakajima, K., and Pfeifer, R. (2012). Bootstrapping perception using information theory: Case studies in a quadruped robot running on different grounds. *Advances in Complex Systems J.* 15 (6). [online ready]

Below, we present the abstract and summarize the most important contributions with regard to the goals set in this thesis.

Abstract. *Animals and humans engage in an enormous variety of behaviors which are orchestrated through a complex interaction of physical and informational processes: the physical interaction of the bodies with the environment is intimately coupled with informational processes in the animal's brain. A crucial step toward the mastery of all these behaviors seems to be to understand the flows of information in the sensorimotor networks. In this study, we have performed a quantitative analysis in an artificial agent – a running quadruped robot with multiple sensory modalities – using tools from information theory (transfer entropy and its recently proposed decomposition). Starting from no prior knowledge, through systematic variation of control signals and environment, we show how the agent can discover the structure of its sensorimotor space, identify proprioceptive and exteroceptive sensory modalities, and acquire a primitive body schema. We propose several scenarios in which the agent could utilize this knowledge to: (i) estimate whether changes come from the environment or from the agent's own body; (ii) learn new behaviors; (iii) focus its attention. In summary, we show how the analysis of directed information flows in an agent's sensorimotor networks can be used to bootstrap its development.*

4.1 Minimally cognitive phenomena

We have argued that the first step on the way from reactive to cognitive behavior is to extract and remember regularities in the sensorimotor space that arise from the agent's embodied interaction with the environment. These patterns constitute the raw material for any higher cognitive processes. In this study, we have applied the tools of information theory to uncover the structure of the sensorimotor space in the Puppy robot, as it runs with different gaits on different ground substrates. The specific points relating to understanding of minimally cognitive phenomena are:

- **Learning the body schema.** Looking only at the changes in information flows between motors and sensors under different conditions (different controllers, different environments), we were exploring how much can the robot infer about its body. First, we studied the structure of the sensorimotor space that is invariant to the controller and environment changes. Second, we studied which sensory channels are strongly affected by the motor signals. This provides an alternative view: the agent's body is what the agent can control. These are two complementary viewpoints on the body schema and can have merits for the agent: the former one could be used for self-diagnosis (if the invariant structure changes, this can be attributed to changes in the body), the latter one can be used to bootstrap development—knowing what lies under the robot's control can be used to synthesize the first controllers.

- **Learning about different sensory modalities.** According to O'Regan and Noe [O'Regan and Noe, 2001], it is the SMCs, i.e. the structure of the rules governing the sensory changes produced by various motor actions, what differentiates modalities. We have applied a similarity measure to the information flows and projected the sensors and motors to a 2D space, creating a sensoritopic map (see Appendix D, section 3.4.2, Fig. 12). The resulting map shows a reasonable clustering of angular sensors in active vs. passive joints, pressure sensors, and inertial sensors. Thus, the agent can autonomously learn that its sensory channels belong to different modalities.

- **Proprioceptive vs. exteroceptive modalities.** The notion of body schema as "my body is what is under my control" can be also used to define proprioceptive modalities: the sensory channels which receive a lot of information from the motor channels. Exteroceptors, on the other hand, can be defined as sensory channels sensitive to environmental changes. Applying these definitions to the information flows that the agent measured gives a graded distinction of the sensors. Interestingly, only the angular position sensors in the active joints fell clearly into the proprioceptive region. The other sensors—most of which would be labeled as proprioceptors using a standard "textbook" definition—were found to be more sensitive to the environment (see Appendix D, section 3.4.1, Fig. 12). We have thus shown that proprioception and exteroception can be considered a continuum and that an agent can autonomously find out about these properties of its sensors. This knowledge can then be exploited to estimate whether changes in the patterns observed in the sensorimotor space were more likely to be caused by changes in the environment or in the body.

- **Sensor quality and focus of attention.** We defined *predictive capacity* of every sensor as its aggregate capability of predicting future states of other sensory channels. If a particular sensor has a high predictive capacity, then it acts as a "hub" that effectively taps into many prominent information flows. This can be a rough indicator of the sensor's quality or utility and the agent could for instance devote more attention to this channel. Conversely, a sensor with a low score could receive less attention or be marked for replacement. (see App. D, 3.4.3 and Fig. 13)

4.2 Toward applications

The outcomes of this study have a significant application potential with respect to making robots more autonomous and resilient. As we have explained, automatic synthesis of a robot model (body schema) can be used to create controllers as well as for self-diagnosis. Moreover, the model can be seamlessly adapted if circumstances change. In addition, we have sketched a new method of detecting changes in the environment: rather than considering individual sensory features, information flows between sensory and motor channels can serve as features, thereby strongly exploiting the body to prestructure the sensory inputs (cf. [Iida and Pfeifer, 2006]).

Chapter 5

Path integration from multimodal proprioceptive sensory information

This chapter refers to the publication [Reinstein and Hoffmann, 2011], enclosed in Appendix E.

Reinstein, M. and Hoffmann, M. (2011). Dead reckoning in a dynamic quadruped robot: Inertial navigation system aided by a legged odometer. In *IEEE Int. Conf. Robotics and Automation (ICRA)*, pages 617–624.
Note: The contribution of both authors to this work was equal.

Below, we present the abstract and summarize the most important contributions with regard to the goals set in this thesis.

Abstract. *It is an important ability for any mobile robot to be able to estimate its posture and to gauge the distance it travelled. The information can be obtained from various sources. In this work, we have addressed this problem in a dynamic quadruped robot. We have designed and implemented a navigation algorithm for full body state (position, velocity, and attitude) estimation that does not use any external reference (such as GPS, or visual landmarks). Extended Kalman Filter was used to provide error estimation and data fusion from two independent sources of information: Inertial Navigation System mechanization algorithm processing raw inertial data, and legged odometry, which provided velocity aiding. We present a novel data-driven architecture for legged odometry that relies on a combination of joint sensor signals and pressure sensors. Our navigation system ensures precise tracking of a running robot's posture (roll and pitch), and satisfactory tracking of its position over medium time intervals. We have shown our method to work for two different dynamic turning gaits and on two terrains with significantly different friction. We have also successfully demonstrated how our method generalizes to different velocities.*

5.1 Minimally cognitive phenomena

This study provides next steps on the path "From locomotion to cognition" in the following ways:

- **From correlation to functional relationships.** In the previous study (Ch. 4), we showed how prominent relationships in the sensorimotor space can be discovered. In this study, we were interested in a specific relationship: one between an external variable—stride length—and all the sensory channels.[1] Then, we provided the next step, i.e. further elaborating and then using the relationships discovered. Sensory features that correlated most strongly with stride length were selected and a linear regression function that combined them into a stride length estimate was derived, giving rise to a multimodal legged odometer. That is, we showed an example of a procedure that can be employed by an autonomous agent: investigate relationships between a variable of interest and the sensory (or sensorimotor) space, select the signals with the strongest relationships, and work them out into a function.

- **Locomotor body schema.** Humans, other mammals, and also arthropods are reported to be able to perform path integration: estimating the distance travelled without relying on an external reference (dead reckoning is the engineering term for this) [Etienne and Jeffery, 2004, Durgin et al., 2009, Wittlinger et al., 2006, Yvanenko et al., 2011]. Odometers (step integrators) were found to play an important part in this capability. To estimate the length of the step (or stride), the animal requires a body representation of some sort ([Yvanenko et al., 2011] mention: knowledge about intrinsic dynamics of limb segment motion, relationships between gait parameters and body proportions). In our quadruped robot, we developed one possible solution to the problem: an implicit (data-driven, black-box) model that linearly combines features from multiple sensors from the robot's legs to a stride length estimate.
- **Integrating information over time.** In this case study, the agent "breaks the here-and-now barrier", which we have listed as an important hallmark of cognitive development. In this case, the agent was mainly concerned with the past by integrating the path it has travelled in the past couple of minutes. In fact, "navigation based on dynamic ego-centric path integration" is one of the guidelines that a developmental cognitive system should satisfy [Vernon et al., 2010b]. Furthermore, the implementation of the state estimation with a Kalman filter matches with the vehicle proposed as an emulator by [Grush, 2004] (see section 1.3.1).[2]

5.2 Toward applications

A novel architecture for dead reckoning in legged robots relying on self-motion cues only (no external reference) was presented. State estimation was achieved through a combination of an Inertial Navigation System and a data-driven multimodal odometer. This solution can in principle be applied to any autonomous ground vehicle. In particular, it is suited to platforms with complicated kinematics and dynamics, which are hard to model analytically. The specific contributions are:

- A legged odometer based on multimodal information from the robot's legs was presented. A linear function of the input features was sufficient for a successful estimation. We attribute this to the richness of the sensory set and active perception through body dynamics.
- The architecture consisted of a combination of an analytical model for the inertial navigation system and a data-driven architecture for the legged odometer. This combination matches the relative ease of analytical modeling of the inertial sensors, as opposed to the difficulty of modeling of odometry in a legged robot (whose motion, in addition, includes slippage).
- The architecture generalized to different speeds and was tested on different terrains.

[1] The implementation details were different than in Ch. 4. First, the sensory signals were not raw time series, but were compressed into features. Second, we have used simple linear correlation rather than transfer entropy.

[2] Nevertheless, we have to say that the Inertial navigation system and the Extended Kalman filter implementation were engineering solutions that incorporated a lot of prior knowledge about the dynamics of the nonlinear system and the noise characteristics of the sensors.

Chapter 6

Using sensorimotor contingencies for terrain discrimination and adaptive walking behavior

This chapter refers to the publication [Hoffmann et al., 2012] which is enclosed in Appendix F.

Hoffmann, M., Schmidt, N., Pfeifer, R., Engel, A.K., and Maye, A. (2012). Using sensorimotor contingencies for terrain discrimination and adaptive walking in the quadruped robot Puppy. In Ziemke, T., Balkenius, C., and Hallam, J., editors, *From animals to animats 12: Proc. Int. Conf. Simulation of Adaptive Behavior (SAB), Odense, Denmark*, Vol. 7246 of LNAI, Springer, pages 54-64.

Below, we present the abstract and summarize the most important contributions with regard to the goals set in this thesis.

Abstract. *In conventional "sense-think-act" control architectures the behavior of artificial agents critically depends on a reliable recognition of the state of the agent and the environment. Perception is reduced to a passive collection of sensory information, followed by a mapping onto a prestructured internal world model. For biological agents, Sensorimotor Contingency Theory (SMCT) posits that perception is not an isolated processing step, but is constituted by knowing and exercising the law-like relations between actions and resulting changes in sensory stimulation. We present a computational model of SMCT for controlling the behavior of a quadruped robot running on different terrains. Our experimental study demonstrates that: (i) Sensory-Motor Contingencies (SMC) indeed provide better discrimination capabilities of environmental properties than conventional recognition from the sensory signals alone; (ii) discrimination is further improved by considering the action context on a longer time scale; (iii) the robot can utilize this knowledge to adapt its behavior for maximizing its stability.*

6.1 Minimally cognitive phenomena

This study is the next step on the "cognitive ladder" that the Puppy robot is "climbing". A record of past experience in the sensorimotor space is used to inform action selection: the robot learns to estimate the effects of the application of different gaits in different contexts and uses this information to choose the actions that maximize a reward signal. The specific points addressed in this study were:

- **Storing sensorimotor experience.** We have employed a model presented in [Maye and Engel, 2011] and adapted it to our situation. Raw sensory signals were compressed into features (analogous to the "Path integration" case study) for every 2 second interval (an epoch). We used 10 features and quantized them into only two levels. Together with the action used (the gait) the features formed an action-observation pair and were stored in an associative memory. In addition, a history of up to 4 epochs was considered and stored. Thus, in this study, a rather exhaustive approach to remembering sensorimotor experience is used: the agent does not try to explicitly extract the structure of the sensorimotor space and store it in a compressed form; instead, every new action-observation combination is added to the memory. Although the theoretical dimension of the sensorimotor space is enormous[1], due to the constraints imposed by the morphology of the robot's mechanical and sensory system, the nature of the interaction with the environment, the action repertoire, and the action selection algorithm, only a small portion of the theoretical state space is visited.[2] This in accordance with previous findings on how sensorimotor information is structured through embodiment [Lungarella and Sporns, 2006]. That is, the regularities in the sensorimotor space help us to successfully cope with the curse of dimensionality.

- **Embodied categorization and object-related SMCs.** Perceptual categorization is a hard problem. However, through embodied interaction with the environment and active generation of sensory stimuli, it can be greatly simplified (see "Embodied categorization" in Appendix A). In our study, when the robot runs on different grounds, only certain, prestructured, stimuli are induced in the sensory modalities. In addition, the particular action used at every moment—the gait—co-determines what will be sensed. We demonstrate this effect by showing the improvement in ground classification when data generated by different gaits are classified separately. Furthermore, this time on a different and more complex robot, we again confirm the hypothesis (put forth in [O'Regan and Noe, 2001] and tested in a simple robot in [Maye and Engel, 2011]) that object categorization (the ground being the object here) is improved if longer sensorimotor sequences are considered (specific object-related SMCs arise).

6.2 Toward applications

As we have briefly reviewed in section 1.7.2, there is a need for more autonomy and flexibility if robots are to independently operate on longer time scales in unknown environments. For unmanned vehicles, perception of the environment and classification into traversable vs. non-traversable terrain remains a challenge. Traditional approaches rely on passive long-distance perception using high resolution sensors and mapping onto predefined representations of traversability of the terrrain (occupancy grids). In contrast, in our approach: (i) the terrain is perceived through a multimodal collection of "tactile sensors": pressure sensors on the feet,

[1] For a history length h, N actions in the repertoire, S sensory features with 2 values per feature, the state space dimension is $(N*2^S)^{h+1}$. For $h=0$, that is taking the current action-observation pair only, and 9 actions in the repertoire, this gives $9*2^{10}=9.216$ possibilities, for $h=1$, it is already 84.934.656 states.

[2] In the simulator, we have collected data from more than 60.000 epochs per environment. For the shortest history ($h=0$, theoretical state space size: 9.216), only 2 to 4% of possible states was actually visited on the flat grounds, and about 15% on the rough terrain, where the interaction was less structured.

accelerometers, and angular position sensors on passive compliant joints; (ii) information is obtained actively while the robot physically interacts with the ground [3]; (iii) actions that gave rise to the sensory stimulation enter the classification; (iv) discrimination capability is further improved if longer sequences of interaction are considered. In this way, an advantageous transformation of the input space for classification was achieved and a minimal resolution of individual sensory channels (only 1 bit) was sufficient for successful terrain discrimination. Then, we have shown how the robot can apply the discrimination ability to select appropriate gaits for the different ground substrates.

In summary, no model of the robot or the environment is provided from the outside. Learning proceeds incrementally, employs redundant sensory information, and could be directly deployed in a long-term adaptation scenario. We are convinced that this viewpoint could be successfully applied in unmanned vehicle terrain perception and will lead to improved robustness and autonomy of these vehicles.

[3]Therefore, the sensory information induced is more directly relevant to the traversability of the given terrain (as opposed to visual features). In addition, the information sampled by the multimodal sensory set was prestructured by the body interacting with the ground (cf. Information theoretic implications of embodiment in Appendix A).

Chapter 7

Moving target seeking with forward and inverse models

This chapter refers to the publication [Oses et al., 2010] which is enclosed in Appendix G.

Oses, N., Hoffmann, M. and Koene, R. A. (2010). Embodied moving-target seeking with prediction and planning. In Corchado, E., Romay, M. and Savio, A., editors, *Proc. Hybrid Artificial Intelligence Systems (HAIS), San Sebastian, Spain, Part II*, Volume 6077/2010 of LNCS, Springer, pages 478–485.

Below, we present the abstract and summarize the most important contributions with regard to the goals set in this thesis.

Abstract. *We present a bio-inspired control method for moving target seeking with a mobile robot, which resembles a predator-prey scenario. The motor repertoire of a simulated Khepera robot was restricted to a discrete number of 'gaits'. After an exploration phase, the robot automatically synthesizes a model of its motor repertoire, acquiring a forward model. Two additional components were introduced for the task of catching a prey robot. First, an inverse model to the forward model, which is used to determine the action (gait) needed to reach a desired location. Second, while hunting the prey, a model of the prey's behavior is learned online by the hunter robot. All the models are learned* ab initio, *without assumptions, work in egocentric coordinates, and are probabilistic in nature. Our architecture can be applied to robots with any physical constraints (or embodiment), such as legged robots.*

This study complements our previous studies by specifically targeting the future. With respect to the previous studies, a number of simplifications has been made. First, unlike in the previous studies that involved a real quadruped robot, we have used simulated Khepera robots. However, to facilitate the transition to the legged robot in the future, we have prepared only a small repertoire of "gaits" for the wheeled robot. We are currently transferring the architecture to the simulated quadruped robot (preliminary, unpublished results)[1]. Second, as planning of motor actions was our focus in this study, sensing was greatly simplified: the robot had access to its GPS coordinates as well as those of the "prey" robot and was converting them to an ego-centric reference frame.

[1]In Fig. 2.1, the time scale used in the quadruped robot are depicted – to allow for comparison with the time scale in the other case studies.

7.1 Minimally cognitive phenomena

This study constitutes the last step on our path "from locomotion to cognition"—incremental cognitive development in a mobile robot. We prepared a scenario in which a "hunter" robot needs to catch its conspecific "prey" robot. The scenario was manipulated in order to investigate under which conditions becomes more elaborate planning necessary and what are the best candidates for the implementation. The "hunter" robot was progressively forced by the task-environment to employ less reactive and more cognitive strategies. Finally, it arrived at a multi-step planning architecture: a "decoupled" forward model, which can be executed independently. This corresponds to the "cognitive hallmark" proposed by Clark and Grush [Clark and Grush, 1999] (see section 1.3.1). The specific points addressed were:

- **Learning a forward model.** A forward model predicting the robot's change in position and orientation was learned through random exploration of the effects of different gaits. An egocentric reference frame was used and no prior knowledge about the platform (such as its kinematics or dynamics) were necessary.
- **Goal state and inverse modeling.** In this study, we were for the first time dealing with goal states at a future time step—the goal being to come as close as possible to the prey robot. That is, in order to reach the goal state, an inverse model to a forward model became necessary. This was obtained through simple Bayesian inference.
- **Multi-step planning.** We have presented the robot with different scenarios: whereas a simple application of the inverse model yielded satisfactory results in some scenarios, in others it did not suffice. There, we have studied how multistep planning can improve the results. In order to cope with a combinatorial explosion of possibilities, a heuristic best-first-search was implemented.
- **Extending modeling to other agents.** The utility of explicitly modeling a part of the environment (the "prey" agent) is evaluated and successfully incorporated when it improves the agent's performance. In this way, the agent extends the space of its cognitive processes to other agents.

7.2 Toward applications

The architecture presented has the components necessary to implement moving target seeking by an autonomous vehicle. Due to the fact that there are no assumptions regarding the vehicle's motion, the same method is easily transferable to any mobile robot. In fact, the target could be also any other object or a person, for instance. The requirement is that its position needs to be sensed. The models are probabilistic and can be learned from scratch. We have presented solutions of different complexity that can be chosen depending on the task requirements; fast response can be traded for longer lookahead.

Chapter 8

Discussion, Conclusion, Future work

This chapter will be opened by a discussion. Then, a summary of contributions of this work to cognitive sciences and robotics will follow. Finally, we will outline the most important limitations and sketch possible remedies in the form of future research agenda.

8.1 Discussion

Individual case studies have their own discussion sections (in their full version in the Appendix). In what follows, we will first focus on what was at the heart of our investigations: how the regularities in the sensorimotor space can be discovered and stored to later provide behavioral advantages to the agent. Then, we will discuss on the implications and utility of the "minimally cognitive building blocks" that we have explored in this work.

Note that in this section, we will not consider the "Walking & speed adaptation" case study, since in this one only a reactive architecture was present—no sensorimotor relationships were extracted and stored by the agent.

8.1.1 Extracting sensorimotor relationships

Animals and robots alike are faced with multidimensional streams of stimulation that impinge on their sensor arrays. The actuator commands needed to control their complex bodies are of high dimensionality as well. These uninterpreted sensorimotor sequences constitute the raw material for every agent to learn about its interaction with the world. Our goal has largely been to investigate different ways of tackling this raw stream in order to discover some regularities that the agent can use to improve its behavior. The number of options is large. Below we sketch some of the axes that need to be taken into account and point to their instantiation in our case studies[1]. Afterwards, we will discuss some of the implications of the different choices and conclude with a discussion of the relationship to the field of system identification.

- **Sensory-sensory vs. motor-sensory relationships.** The structure of the sensorimotor space as a whole was analyzed in the "Information flows in S-M space" study. In the "Path integration" case study, the relationship between sensory features and an external variable (stride length) was studied. In the "Terrain discrimination" study, action-observation

[1] The short names used are introduced in section 2.2.

(motor-sensory) pairs were used. The "Moving target seeking" study was explicitly employing a forward model—a relationship between two sensory states (current and future) and a motor command. One can say that both, sensory-sensory and motor-sensory, relationships are important. The former can be employed for optimal state estimation, as we have done in the "Path integration" study. Even there, however, the inclusion of the motor modality can be critical for performance: the odometers developed were gait-specific (motor-specific). We have arrived at similar conclusions in the "Terrain discrimination" study, where the action component can significantly improve ground classification. Motor-sensory relationships become indispensable when planning of actions is needed. Nesting them can give rise to a an internal simulator of the agent's interaction with the environment.

- **Two-dimensional vs. multidimensional relationships.** In some case studies ("Information flows in S-M space", "Moving target seeking"), we have analyzed the sensorimotor space by looking at relationships between pairs of variables (motor or sensory channels). In the "Path integration" study we studied mappings from multiple sensory variables to a single external variable. Finally, in the "Terrain discrimination" study, a more holistic approach was used, in which the whole sensorimotor space was considered at once (concatenated into a single action-observation vector).

- **Linear vs. nonlinear relationships.** With the exception of the "Path integration" case study, where we have specifically targeted linear relationships, in the rest of the work, we have dealt with joint or conditional probability distributions, which account for nonlinear relationships as well.

- **Relationships in time and directed vs. undirected relationships.** In the "Path integration" and "Terrain discrimination" case study, the motor and sensory time series were naturally parsed in time according to the periodic character of the robot's locomotion. Within this time interval (1 or 2 seconds), the (undirected) relationships between the modalities were inspected. In the other two case studies ("Information flows in S-M space","Moving target seeking"), directionality was introduced by manipulating a time lag between individual time series—the relationship between the past value in one channel and a future value in another channel was studied. This lends itself to a causal interpretation—the past event bringing about the future one—, but this is an assumption that needs to be further verified, for example using interventional methods [Ay and Polani, 2008, Pearl, 2000].

- **Preprocessing of raw data.** In the "Information flows in S-M space" case study, we start with raw time series and then calculate conditional probability distributions which serve as a basis for the information flow calculations. In the other case studies, a higher abstraction level is used: features which compress the time series in each channel into a single number for a given time interval (a period of locomotion for example).

In summary, all the choices listed above impact what will be learned about the structure of the sensorimotor space. From our explorations, we may derive some desired properties of a measure or method that will be used to extract relationships in sensorimotor space: (i) it should encompass sensory-motor as well as sensory-sensory relationships; (ii) it should be sensitive to linear *and* nonlinear relationships; (iii) it is advantageous if directionality and the time component are considered. Looking at pair-wise relationships between time series and compressing them into features constrains the relationships that can be potentially uncovered and represent designer's bias. On the other hand, computational complexity as well as data set size cannot be neglected and multidimensional joint probability distributions—which would encompass most of the information contained in the sensorimotor space—are practically hard to attain.

Learning sensorimotor relationships vs. system identification

To what extent does the endeavor of extracting invariants in the sensorimotor space overlap with the system identification field? System identification (e.g., [Ljung, 1999]) covers a broad range of methods to extract a model of a dynamical system. We want to mainly focus on models of mechatronic systems, in particular robots. The models may have different forms, from gray-box—where structure is provided to the model based on knowledge about the physics of the system, for instance—to black-box, where input-output mappings are directly approximated. In addition, there are numerous dedicated procedures for exciting the system, such that appropriate data for generating the model can be obtained. Some of the problems we have addressed would fit under the system identification scope. In particular, in the "Path integration" and "Moving target seeking" case studies, we were trying to approximate specific mappings (such as from sensory features to stride length). In the latter study, where a Bayesian network was used, the structure of the network was given from the outside using knowledge about the problem. Thus, one could call it a gray-box model.

On the other hand, the "Information flows in S-M space"[2] and "Terrain discrimination" case studies depart from a traditional system identification setting. First, the problem is much less constrained and it is not a specific mapping that we are looking for. What are the relevant contingencies in the sensorimotor space is first to be discovered. Second, in particular in the "Terrain discrimination" study, the "identification" of the system proceeds on the run, while optimizing the behavior. That is, no dedicated data collection phase is needed for acquiring a model of the system. Third, a strictly situated perspective is followed. That is, the only information available is what the robot can collect from its own sensors (and motors): no external measurements are taken. Related to this, the model obtained necessarily incorporates not only the mechanical system, but also the morphology (shape, type, properties) of the motor and sensory apparatus. This contrasts with traditional engineering models, where these components would be modeled separately.

8.1.2 Storing sensorimotor experience

The next logical step after picking up the regularities in the sensorimotor space is to store them. There are many, some of them conflicting, requirements on such a representation[3]. First, let us go through the different implementation types we have used in our case studies. The "Information flows in S-M space" was focusing on quantifying relationships in the sensorimotor space, not on storing and using them. In the "Path integration" study, we are concerned with the legged odometer part only[4]: the multimodal stride length estimator had a form of a regression function. In "Terrain discrimination" and "Moving target seeking", the representation was based on conditional probabilities. We will go through the properties of the architectures and discuss their implications. A summary of their features will be provided at the end.

Regression function

In order to obtain a legged odometer in the "Path integration" study, we were looking for sensory features that strongly correlate with the variable of interest: stride length. A set of such features was selected and the coefficients of a regression function (which maps the features into stride length) were learned offline from the data. A regression function is a very parsimonious

[2]For a discussion of this particular study's relation to system identification, please see the Discussion in Appendix D.

[3]Representation is meant as a synonym to storage. It does not imply that what is being stored is a representation of the outside world – see Section 1.8.

[4]The whole dead reckoning system implemented with a Kalman filter will have different properties, but that is not at the center of our interest, as this was largely a standard engineering solution.

way of storing a relationship between variables—only the coefficients that define the mapping are needed. On the other hand, it is a single-purpose mapping, which does not account for uncertainty and its inverse is also not available.

Bayesian network

In the "Moving target seeking" study, we also selected the relationships of interest: change in the robot's position and heading resulting from the application of a gait. These were represented with a small Bayesian Network (BN), which contained the following three relationships: $P(Distance|Gait)$, $P(Angle|Gait)$, and $P(Heading|Gait)$. An ego-centric coordinate system was used (i.e. the robot's current position was always at the origin); the conditional probabilities thus tell what is the likelihood of the robot moving a distance d, at an angle a, with the next heading h (with respect to the original body axis) if it applies gait g for one time step. This formulation is essentially equivalent to a probabilistic forward model of the form $P((Position, Orientation)_{t+1}|$ $(Position, Orientation)_t, Gait_t)$.[5] The next position and orientation can thus be predicted. Furthermore, these predictions can be chained and multi-step planning is easily possible.

The BN parameters were learned offline from data obtained while the robot was randomly executing different gaits. The data was complete, the structure of the network known and the prior probability distribution for the gaits was uniform. Maximum a posteriori (MAP) learning therefore reduced to maximum-likelihood parameter learning. In order to know which gait the agent should take to move a certain distance at a certain angle, the inverse model $P(Gait|Distance, Angle)$ can be obtained through inference from $P(Distance|Gait)$ and $P(Angle|Gait)$.

Conditional probability distributions in associative memory

Whereas the above-mentioned solutions are largely standard, in the "Terrain discrimination" case study, we have used a new architecture which was proposed in [Maye and Engel, 2011] as a computational model of SMCs. Rather than representing a selected relationship from the sensorimotor space, we attempted to encompass the sensorimotor experience of the agent as a whole. The basic idea is to consider actions and resulting changes in sensory signals in an integrated manner and to keep a record of sequences of actions and sensory observations. For each epoch, the action a (the gait in this case) and a vector of n sensory features observed during execution of a are concatenated to a single vector $ao(t) = [as_1s_2 \dots s_n]$ that we call an action-observation pair. Sequences are stored as a vector $c^h = [ao(t), ao(t-1), \dots ao(t-h)]$; we used $h = 0 \dots 4$. From its experience, the robot learns the conditional probability distributions $P^h(ao(t+1)|c^h(t))$, i.e. the probability of experiencing a particular action-observation pair in the next time step given a finite history h of previous pairs.

This approach seems to be vulnerable to the curse of dimensionality. The theoretical size of this state space is $(N * b^S)^{h+1}$, where N is the number of actions, S the number of sensors, b is the resolution of each sensor, and h the history length. We have compressed the signals from 11 sensory channels into 10 features with only 1 bit (2 values) resolution each. Still, for $h = 0$, that is taking the current action-observation pair only, and 9 actions in the repertoire, this gives $9 * 2^{10} = 9.216$ possibilities; for $h = 1$, it is already 84.934.656 possible states. Systematically exploring the whole state space and representing it with a single probability distribution thus does not come into question. Therefore, only the contexts that were actually encountered are stored in

[5]The difference is that in our implementation, where three conditional probabilities are used, we assume their conditional independence. This is a so-called Naive Bayes approach, which is often quite effective even when the attribute values are not conditionally independent [Mitchel, 1997,Russel and Norvig, 1995].

an associative memory (the key is the context c^h). There, the local probability distribution, conditioned on the context, is stored and incrementally updated. The representation used resembles an n-th order Markov model. However, it is a distributed and sparse variant of it—only local probability distributions are stored. That is, no model (and transition matrix) of the whole state space exists.

How much of the state space is actually visited, i.e. how sparse is the representation? In the simulated version of the quadruped robot, we have collected data from more than 60.000 epochs per environment. For the shortest history ($h = 0$, theoretical state space size: 9.216), only 2 to 4% of possible states was actually visited on the flat grounds, and about 15% on the rough terrain, where the interaction was less structured. The sparseness is to be attributed to the constraints imposed by the interaction of the robot with the environment. This is in accordance with previous findings on how sensorimotor information is structured through embodiment [Lungarella and Sporns, 2006] (cf. App. A for additional accounts of "information self-structuring" through embodiment). The explosion of the dimensionality of the model is further prevented by the action selection algorithm (see App. F for details).

Forward modeling, with uncertainty, is directly supported by this implementation: the robot can use the local probability distribution to estimate the likelihood of future states. An inverse model—what is the action that would most likely bring me from a current state to a desired state—can likewise be obtained from the local probability distribution.

Summary of architectures

A summary of some of the features of the different architectures in our case studies is provided in Table 8.1. Let us go through each of them in turn. First, whereas a regression function is a continuous mapping (Ch. 5, "Path integration"), the conditional probabilities used in the two other case studies were stored in a discretized form. However, this is only one option—they could also be approximated using a continuous model, such as finite mixture models [Figueiredo and Jain, 2002]. Second, whereas regression functions do not incorporate uncertainty, probability distributions naturally do. Third, inverse mappings can be obtained through Bayesian inference from conditional probabilities in the other direction (under some conditions). Fourth, all the architectures used can theoretically also store any relationships between variables in time. However, Bayesian networks offer tools directly tailored for relationships in time sequences of variables—these are Dynamic Bayesian Networks. Hence, the two probabilitic models we used (Ch. 6 and 7) can easily incorporate relationships in time and we have also used them in this way. Fifth, the regression function (Ch. 5) as well as the Bayesian network (Ch. 7) were learned offline from the data. The "prey" (the robot the "hunter" has to catch) model is learned online though (see section 3 in App. G for more details). The associative memory implementation (Ch. 6) is designed for incremental learning—the local probability distributions that match the current context are updated with the new experience.

Finally, let us contrast how versatile and compressed the different representations are. Selecting a single mapping and describing it with a regression function is a parsimonious but not very versatile option. On the other hand, joint or conditional probability distributions (Ch. 6 and 7) can preserve lot of original information from which various relationships can be extracted on demand (e.g. inverse relationships through Bayesian inference). However, for a system with an n-dimensional sensorimotor space, n-dimensional joint probability distributions would be required. Furthermore, we are interested in relationships in time as well. Therefore, some decisions need to be made on how to compress the information. One option is to select the relationships of interest and learn only these, as we have done in Ch. 5 with a regression function and in Ch. 7 with a Bayesian network. In the latter case, we have provided the structure of the network from the outside. An alternative is to learn this structure from the data (e.g., [Friedman et al., 1999]). In fact,

Attributes	Ch. 5	Ch. 6	Ch. 7
Continuous / Discrete	C	D	D
Accounts for uncertainty	no	yes	yes
Inverse mapping	no	yes	yes
Time dependencies	no	yes	yes
Incremental learning	no	yes	partly
Versatility	low	high	high
Storage size	small	significant	medium

Table 8.1: Storing sensorimotor experience. The columns correspond to the individual case studies: Path integration (Ch. 5 and App. E): regression function, Terrain discrimination (Ch. 6 and App. F): conditional probability distribution in associative memory, Moving target seeking (Ch. 7 and App. G): Bayesian network. The rows schematically list some attributes of the architectures used to store the sensorimotor relationships.

our analysis of the information flows ("Information flows in S-M space") could aid learning of the structure by providing an initial pruning of the relationships between variables. The approach we used in the "Terrain discrimination" study (Ch. 6) provides another alternative, as discussed in section "Conditional probability distributions in associative memory" under section 8.1.2. There, we store the whole sensorimotor experience, but using a sparse representation. That is, only the contexts (particular sensory and motor values) actually experienced by the agent are stored. This representation is on one hand holistic—it encompasses the whole sensorimotor space—, on the other hand, it is local—information is available only about previously visited contexts. Extrapolation or generalization to unknown, previously unseen, states using this architecture is a future research topic.

8.1.3 Body schema, forward models, or SMCs?

We have set out in the Introduction to investigate bottom-up development of minimally cognitive abitilities and we have selected three "building blocks" to help us in this endeavor: body schema, forward internal models, and sensorimotor contingencies (SMCs) (section 1.6). We have explored them in different disguises in our robotic case studies; an overview is provided in section 2.3.2. What can we now say regarding the utility of each of these concepts for cognitive science and for cogntive developmental robotics in particular?

As reported by Rochat [Rochat, 1998], infants spend substantial time in their early months observing and touching themselves. Through this process of babbling, intermodal redundancies, temporal contingencies and spatial congruences are picked up. This basically encompasses all the low-level relationships that an agent can learn during its early development. However, as we have analyzed in the previous sections (8.1.1, 8.1.2), this space is too large. Therefore, in order to bootstrap its development, an agent needs to focus on some subspaces of the sensory-motor-time space. The three concepts: body schema, forward models, SMCs are such subspaces that may be particularly relevant to an agent (see section 2.3.2).

As we have extensively argued, the body has a key influence on the agent's behavior as well as on the information that enters its brain/controller (Appendix A). Therefore, it can definitely bring advantage to the agent if it can pick up the regularities that are induced by its body. The concepts of body schema and body image are used in this context. However, at the moment they serve more as "umbrella concepts" for a multitude of body representations that animals and humans develop and use (cf. e.g. [de Vignemont, 2010]). The synthetic methodology allows us to explore these concepts in more concrete terms. In the "Information flows in S-M space" study, we investigate two possibilities fo a body representation in the quadruped robot. First, we study the structure of the sensorimotor space that is invariant to changes in the motor commands and the environment. Second, we study which sensory channels are strongly affected by the motor signals. This provides an alternative view: the agent's body is what it can control. Both viewpoints can have merits for the agent: the former one could be used for self-diagnosis (if the invariant structure changes, this can be attributed to changes in the body), the latter one can be used to bootstrap development—learning the first behaviors.

Forward model is another type of mapping that can be useful to the agent. It can be used to predict the next sensory state or even to simulate whole sensorimotor loops covertly. It is concretely defined and can be instantiated at any abstraction level (i.e., not only for low-level motor control, where the existence of forward internal models is subject to a heated debate). Thus, we find it a useful and easy to deploy building block for minimally cognitive phenomena.

Similarly to a body schema, SMCs are a concept that has its origin in psychology, philosophy, and—since SMCT[6] is much newer than body schema—also neuroscience. Perhaps due to the origin in "non-mathematical" disciplines, the theory is not worked out to that level of detail that would allow direct testing and implementation in artificial agents. Nevertheless, SMCs—structure of the rules governing sensory changes produced by various motor actions—are also concerned with a specific mapping in the sensorimotor space. As we have argued in section 1.6.4 and 2.3.2, a forward model may in fact be an instance of such a mapping. The structure of these mappings would constitute the SMCs. In the "Terrain discrimination" we have investigated one possible interpretation and implementation (developed in [Maye and Engel, 2011]). There, no attempt is made to explicitly extract the structure; instead the sensorimotor experience is stored in an exhaustive fashion in an associative memory. The structure is thus implicitly present, but not explicitly articulated.

Finally, while these (more or less) specific types of subspaces or mappings may provide guidance to a cognitive agent for which relationships to look, we have offered an additional alternative in the "Information flows in S-M space" case study. There, we have looked at the sensorimotor space as an undifferentiated, "synesthetic" space and the agent was simply extracting the strongest, most salient, relationships. These can then be selected and further elaborated into functional relationships, for example. In many cases, they will overlap with one of the building blocks described above. However, other patterns can be important. For instance, we have not only looked at patterns that are invariant, but also at those that change. The agent can learn about the sensorimotor flows that are sensitive to the environment, for instance, and focus on these in order to detect terrain changes.

8.2 Conclusion

Following the synthetic methodology, our explorations provide on one hand inroads into the understanding of minimal cognitive phenomena, on the other hand, they serve as demonstrators how cognitive developmental robotics can lead to more autonomous and versatile robots that can do useful work. We will summarize our contributions to these areas below.

8.2.1 Contributions to cognitive sciences

In this dissertation, our focus was on autonomous cognitive development in mobile, mainly legged, robots. We have engaged the robots in a number of scenarios that formed a developmental pathway from reactive to increasingly cognitive behavior. Starting from learning to walk

[6]Sensori-Motor Contingency Theory.

and speed adaptation (Ch. 3 & App. C), we have devoted the next case study (Ch. 4 & App. D) to a detailed analysis of the sensorimotor space: the raw material for any cognitive processes. Afterwards, we have presented the robot with three scenarios that require some integration of information: beyond simple stimulus-response behaviors and thus "breaking the here-and-now barrier". These scenarios were path integration (Ch. 5 & App. E), terrain discrimination and gait adaptation (Ch. 6 & App. F), and moving target seeking (Ch. 7 and App. G). In order to successfully master these scenarios, the robots had to discover, store and later recall the regularities they experienced in the sensorimotor space. The scenarios were inspired by skills that were observed in lower animals and serve as instances of the simplest behaviors that we would consider cognitive. All of the tasks were related to locomotion, giving rise to a "from locomotion to cognition" pathway.

The contributions of individual case studies were discussed in the individual chapters (in the sections "Minimally cognitive phenomena"). The overarching theme was to understand how much can an autonomous agent learn about its interaction with the environment in a bottom-up fashion by using raw uninterpreted streams of sensor and motor data only. To this end, we have investigated methods of uncovering the structure of the sensorimotor space. Then, we have experimented with different "cognitive building blocks": body schema, forward internal models, and sensorimotor contingencies. These are "neural vehicles" [Engel, 2011] that are shaped by the agent's interaction with the world. They are not the site of cognition, but their goal is to support the agent in a successful interaction with the environment—guide its actions. We have used different implementations which allowed us to compare their utility, efficiency and limitations for the artificial agent.

The field of interest—cognition, minimal representations, body image and schema—is highly interdisciplinary and diverse. Different disciplines and schools not only hold different views, but also use different terminology. A major contribution of this dissertation is in fact a conceptual and terminological clarification. First, we have compiled two review articles that talk to a multidisciplinary audience ([Hoffmann et al., 2011a], Appendix A and [Hoffmann et al., 2010], Appendix B). Second, we have instantiated the phenomena under investigation in robotic scenarios, thus providing concrete grounds for further discussion of the concepts.

8.2.2 Contributions to robotics

We have summarized the potential of individual case studies in the respective chapters (sections "Toward applications"). Here, we want to elaborate two important themes that were present in multiple case studies and that have substantial potential in robotic applications: (i) automatic robot model acquisition and adaptation, and (ii) terrain traversability detection by mobile robots.

Automatic robot model acquisition and adaptation

Traditionally, robots need models of their bodies (the so-called plant models in control theory) and of the environment they are operating in, in order to function. These models are designed by engineers and they are usually tailored to a particular task. However, robots composed of compliant or deformable elements pose major difficulties for modeling. In addition, if conditions change over time, the models may have to be manually adapted which generates substantial costs. Please refer to section 1.7 or to Appendix B, Section III.A 2) *Model – Benefits and costs* for a more detailed discussion. Therefore, to increase the robot autonomy, versatility, resilience, and to cut down costs on programmers, it is highly desirable that the robots can synthesize, calibrate and adapt their models automatically.

We have made several contributions to this area. First, we have structured and reviewed the work that has been done in this direction in [Hoffmann et al., 2010], Appendix B. Second, in the

"Information flows in S-M space" case study (Chapter 4 and App. D), we have illustrated how a robot can autonomously perform the first steps needed for the acquisition of a model of its body. We have outlined how this model can be exploited for control as well as diagnostic purposes (environment and failure detection). Third, we showed that the boundary between the robot's body and the environment is—from the robot's situated perspective—not always clear. Therefore, no explicit separation of the two needs to be done in a model. We have applied this approach in the "Terrain discrimination" case study (Ch. 6 and App. F). The robot learned the sensorimotor mappings that arise from the interaction with the environment, associated them with a reward, and used this model to select actions. This solution is straightforward, allows for learning in an incremental fashion and can be applied to any robot, provided that it has a multimodal set of sensors. Finally, in the "Moving target seeking" study (Ch. 7 and App. G), a forward model of the robot's behavior (this time focused on displacement) was learned from scratch. The forward model was employed in a planning problem and we have presented solutions of different complexity that can be chosen depending on the task requirements; fast response can be traded for longer lookahead.

Traversability detection in mobile robots

As we have reviewed in section 1.7.2, there has been remarkable progress in the area of unmanned ground vehicle navigation. At the same time, in order to further increase the robots' autonomy, there is a need to replace hard-coded engineered solutions with adaptive ones that rely on learning from interaction with the environment. We have addressed this in the "Terrain discrimination" case study (Ch. 6 and App. F). Unlike traditional approaches that rely on passive perception using long-distance high resolution sensors and mapping onto predefined representations of traversability of the terrrain (occupancy grids), we have applied a different approach. The terrain the robot was traversing was perceived through a collection of "tactile sensors": pressure sensors on the feet, accelerometers, and angular position sensors on passive compliant joints. The information was necessarily obtained actively, while the robot physically interacted with the ground. Therefore, the information obtained in this way was more directly relevant to the traversability of the given terrain (as opposed to visual features, for instance). In addition, the information sampled by the multimodal sensory set was prestructured by the body interacting with the ground (cf. Information theoretic implications of embodiment in Appendix A). In order to take full advantage of this, the actions that gave rise to the sensory stimulation entered the classification. Furthermore, we have shown that the discrimination capability improved if longer sequences of interaction were considered. In this way, an advantageous transformation of the input space for classification was achieved and a minimal resolution of individual sensory channels (1 bit) was sufficient for successful terrain discrimination. We have also shown how the robot can apply this ability to select appropriate gaits for the different ground substrates. We are convinced that this viewpoint could be successfully applied in unmanned vehicle terrain perception and will lead to improved robustness and autonomy of the vehicles.

8.3 Limitations and Future research agenda

In this section, we will point to some limitations of the work presented in this thesis and, wherever possible, we will suggest how these limitations can be overcome in the future.

8.3.1 From sensorimotor regularities to higher-level cognition

In this thesis, we have focused on low-level behaviors and studied how an agent can improve its performance by picking up some regularities in the sensorimotor space. This form of modeling of the interaction with the environment was introduced only when it could provide behavioral advantage to the agent. Therefore, we have stayed at the lowest possible level and avoided introducing explicit representations and models of the world that entail the danger of obstructing direct interaction with the environment (”models of the world simply get in the way“ [Brooks, 1991b]). However, can all raw sensorimotor experience of an agent be stored and efficiently used?

> Over the course of life, a person will have encountered myriad visual attributes and visual stimuli, and each of these will have particular sets of sensorimotor contingencies associated with it. Each such set will have been recorded and will be latent, potentially available for recall: the brain thus has mastery of all these sensorimotor sets. [O'Regan and Noe, 2001]

However, please recall that sensorimotor contingencies denote the *structure* of the rules governing sensory changes produced by various motor actions. An exhaustive storage of all sensorimotor sequences does contain such a structure, but in an implicit form. This approach—exhaustive storage—is adopted in the architecture of Maye and Engel [Maye and Engel, 2011], which we have used in the "Terrain discrimination" study (Ch. 6 and App. F) and analyzed in section 8.1.2. Different objects the robot is interacting with (terrains in our case) induce different (sequences of) sensorimotor combinations. In the learning architecture we used, every unique combination is treated as a unique context. However, since we have shown that the sensorimotor combinations generated through interaction with different terrains can be separated with a classifier, they do contain a different underlying "structure". The alternative would be to abstract these rules in one way or another and store a compressed form only. This would have two desired consequences. First, the data will be compressed and hence less storage space will be required. Second, generalization will be achieved. A method of doing this remains a topic of future explorations. An unsupervised technique, such as a form of clustering or hierarchical clustering (as used in [Ugur et al., 2011], for instance), could be an option. Whether the values/rewards associated with the individual sensorimotor "states" should be part of the abstraction mechanism remains an open question as well.

In fact, the scenario outlined above could provide a natural way of attaining higher levels of cognition. These are typically characterized by symbolic processing of some sort, that is manipulation of some discrete abstract quantities. The abstraction of the regularities in the sensorimotor space could give rise to such quantities (which could be called "proto-symbols") in a bottom-up and thus grounded fashion. A similar scenario is sketched by Pfeifer and Bongard [Pfeifer and Bongard, 2007] or Kuniyoshi et al. [Kuniyoshi et al., 2003]. Whereas in these cases "symbols" emerge through compression of sensorimotor patterns, Grush [Grush, 2004] goes further when he proposes an *articulated model* or *amodal emulator*. That is, rather than abstracting from the "modal" space—the space of sensory and motor modalities—the agent will need to discover that there are underlying state variables (e.g., elbow angle, arm angular inertia, tension on quadriceps) that interact according to the laws of dynamics and mechanics and that some of these variables are measured by the agent's sensors [Grush, 2004]. The Kalman filter is a good example of such a model; a Hidden Markov Model, which consists of hidden states and observables, would be another. Whether this is the case in animals is an open question. However, in our case studies, it is hard to imagine how this could be done without providing some knowledge on the structure of the interactions to the agent.

8.3.2 Manipulating the body morphology and sensory apparatus

We have repeatedly emphasized the constitutive effect of the interplay of brain, body and environment on behavior and cognition. We have studied the effects of changing the "brain" (mainly by applying different coordinated motor commands) and environment (by using different terrains). However, the body morphology remained constant in our experiments. As can be seen in Fig. 8 in Appendix A, the body morphology can be further subdivided into the mechanical and the sensory system. Therefore, our studies could be complemented by a systematic variation of the mechanical system (e.g., by trying springs of different stiffness in the passive joints or by changing the mass distribution) and the sensory system. The type as well as placement of sensors can be manipulated. In the Puppy robot, we have not employed any "distal" sensor modalities like distance sensor or cameras, which are important for the development of anticipatory capabilities. This will be the direction of our future work.

8.3.3 Models of biological phenomena

We have outlined the synthetic methodology used in this thesis in section 2.4 and depicted the methodological approaches spanned by individual case studies diagrammatically in 2.4. Whereas the case studies serve as explorations into the general workings of minimal cognitive phenomena, they only touch upon the synthetic modeling region which stands for models of biological phenomena. However, with additional work, the case studies could be turned into models. In what follows, we will sketch how.

Walking & speed adaptation

In this case study (Ch. 3 and App. C), we have addressed three topics in a quadruped robot: terrain detection, learning gaits, and speed adaptation. These behaviors are very low-level and strongly tied to the particular embodiment of our robot: its morphology and sensory and motor apparatus. Since the robot is a pretty distant relative of any quadruped animal, it is not particularly suited to be a detailed model. Yet, on a slightly higher abstraction level, some correspondences could be established. For example, the arrangement of legs—with two segments and a passive compliant joint connecting them—could be a very gross approximation to the functional morphology of quadruped locomotion. The movement is powered from the hip, the passive joints act as springs. Furthermore, there is only one dominant elastic joint in each leg of some locomoting mammals: elbow joints in fore legs, ankle joints in hind legs[7]. In some gaits, the robot Puppy could thus be used to model certain features of the mechanics of quadruped locomotion and its learning.

Information flows in S-M space

In this case study (Ch. 4 and App. D), we have outlined a number of ways in which an autonomous agent could bootstrap its cognitive development by analyzing the sensorimotor flows under different motor programs and in different environments, using transfer entropy. With little prior knowledge, it could discover which sensors have a proprioceptive or exteroceptive nature or what is the structure of information flows induced by the agent's morphology. While we suspect that processes that serve a similar function are active in animals and humans, the question is whether information-theoretic measures could be employed to structure the sensorimotor space. There is evidence that certain neurons are "computing" entropy or mutual information

[7] Nadja Schilling: personal communication.

(e.g., [Rieke et al., 1997]). However, the question is whether they merely contain states that correspond to mutual information about some other neural states, for instance, or whether they are tuned to do that and whether and how this information is actually used in subsequent processing. To this end, additional empirical evidence is required.

Path integration

In this case study (Ch. 5 and App. E), we have devised and tested a new approach to dead reckoning in legged robots. However, our inspiration came also from the animal kingdom. Humans, other mammals, and also arthropods are reported to be able to perform path integration (i.e. dead reckoning) [Etienne and Jeffery, 2004, Durgin et al., 2009, Wittlinger et al., 2006, Yvanenko et al., 2011]. Scientists are trying to isolate the effects of different subsystems, in particular inertial cues and odometers (step integrators)—the two components that were fused in our system too. While some experiments are able to provide evidence that path integration may be dominated by a particular system (e.g., by manipulating the length of ants' legs, [Wittlinger et al., 2006] provides evidence that they are using odometry), the experiments are mostly on a behavioral level, i.e. the underlying mechanisms performing the calculation remain unclear. Moreover, an open question is how do the animals learn or calibrate these systems that are responsible for their navigation capabilities.

We think that our setup could be further elaborated to test the putative mechanisms that are hypothesized to be active in various animals performing path integration. In robots, the mechanisms responsible for behavior can be much better controlled and manipulated. For instance, we can easily test the effects of the strapdown mechanization algorithm and odometry alone and when fused, or we can relatively easily manipulate the robot morphology. Finally, our system was calibrated by using an external reference system—the distance travelled in every period of locomotion was known during the odometer training phase. It is unlikely that such information is available to animals; instead, they probably have to rely on intermittent external reference information, such as when they reach home or spot a landmark. Calibrating the dead reckoning system under such circumstances would be more difficult, but easily testable in our setup.

Terrain discrimination

The Sensorimotor Contingency Theory (SMCT) has its origin in empirical sciences and is primarily a theory of perception. We have used a computational model of the theory in an artificial system and tested one of the hypotheses of SMCT that object perception is exercised by considering longer sensorimotor sequences (Ch. 6 and App. F). In addition, our implementation integrated the record of sensorimotor experience with a value system and an action selection mechanism. The objective is thus to extend SMCT as a theory of perception to cognition in general. These new articulations of the theory should then be verified on biological systems. These are the goals of the Extending Sensorimotor Contingencies to Cognition project (`http://esmcs.eu`), in the context of which this work has been done.

Moving target seeking

In this case study (Ch. 7 and App. G), we were exploring an embodied moving target seeking (or "predator-prey") scenario. This is a problem that many animals also need to tackle. For example, predictive mechanisms are reported even in simple animals, like in the prey-catching behavior of the spider Portia [Tarsitano, 2006]. Pezzulo [Pezzulo, 2007] provides additional examples. By adding details about particular behaviors to our setup, concrete hypotheses could be tested.

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Appendix A

The implications of embodiment for behavior and cognition: animal and robotic case studies

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The Implications of Embodiment for Behavior and Cognition: Animal and Robotic Case Studies

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Abstract. In this paper[1], we will argue that if we want to understand the function of the brain (or the control in the case of robots), we must understand how the brain is embedded into the physical system, and how the organism interacts with the real world. While embodiment has often been used in its trivial meaning, i.e. 'intelligence requires a body', the concept has deeper and more important implications, concerned with the relation between physical and information (neural, control) processes. A number of case studies are presented to illustrate the concept. These involve animals and robots and are concentrated around locomotion, grasping, and visual perception. A theoretical scheme that can be used to embed the diverse case studies will be presented. Finally, we will establish a link between the low-level sensory-motor processes and cognition. We will present an embodied view on categorization, and propose the concepts of 'body schema' and 'forward models' as a natural extension of the embodied approach toward first representations.

Introduction

Intelligent behavior has always fascinated researchers. Traditionally, intelligence was attributed solely to the control or the neural system. In 'classical' (also Good Old-Fashioned — GOFAI) Artificial Intelligence and cognitive science, the focus was on problem-solving through computation on internal symbolic representations of the world (e.g., Pylyshyn, 1987). In computational neuroscience, the focus is essentially on the simulation of certain brain regions. For example, in the 'Blue Brain' project (Markram, 2006), the focus is, for the better part, on the simulation of cortical columns — the organism into which the brain is embedded does not play a major role in these considerations. However, recently there has been an increasing interest in the notion of embodiment in all disciplines dealing with intelligent behavior, including psychology, philosophy, artificial intelligence, linguistics, and neuroscience. In this paper, we explore the far-reaching and often surprising implications of embodiment for

[1] Parts of the ideas presented in this paper have appeared in previous publications; they will be referenced throughout the text.

behavior and for cognition.

While embodiment has often been used in its trivial meaning, i.e. 'intelligence requires a body', there are deeper and more important consequences, concerned with connecting brain, body, and environment. The behavior of any system is not merely the outcome of an internal control structure (such as the central nervous system); it is also affected by the ecological niche in which the system is physically embedded, by its morphology (the shape of its body and limbs, as well as the type and placement of sensors and effectors), and by the material properties of the elements composing the morphology. This embedding impacts the physical as well as the information (neural, control) processes that all together manifest themselves in a particular behavior (Pfeifer & Bongard, 2007).

Physical constraints shape the dynamics of the interaction of the embodied system with its environment (for example, because of the way it is attached to the body at the hip joint, during walking a leg behaves to some extent like a pendulum) and can be exploited to achieve stability and energy efficiency. We will speak about 'intelligence by mechanics' or 'morphological computation' when morphology and materials take over some of the functions normally attributed to the brain (or the control). A direct link also exists between embodiment and information: coupled sensory-motor activity and body morphology induce statistical regularities in sensory input and within the control architecture and therefore enhance internal information processing (e.g., Lungarella & Sporns, 2006).

The above-mentioned points apply to any agent interacting with its environment, animal or robot. We will present some case studies from biology, however, our selection will be biased toward case studies on robots. The advantage of using robots is that embodiment can be investigated quantitatively: robots are much simpler to manipulate and monitor. That is, first, we can change the control structure without much effort, and we can even manipulate the morphology relatively easily. Second, all sensory stimulations, motor signals, and internal states can be recorded as time series for further analysis. Having discovered some principles or put forth some hypotheses, we can turn back into the biological realm and verify the ideas. Such a method corresponds to the synthetic modeling approach, or 'understanding by building' (Pfeifer & Scheier, 1999; Webb, 2001). At the same time, these principles will enable us to design and build intelligent systems (computer programs, robots, other artifacts) for research and application purposes.

We will demonstrate that embodiment not only plays a crucial part in low-level sensory-motor activities (such as locomotion), but also in capabilities that would be considered cognitive. To illustrate that, we present an embodied view on categorization. Still, we stop short of the so-called higher-level cognitive capabilities such as planning, abstract reasoning, or language. In an effort to bridge this gap, we will sketch how the bottom-up, embodied, approach can be naturally extended to form representations, providing a way to higher-level cognition. The way is through the concepts of 'body schema' and 'forward models'.

We will proceed as follows. First, we will present a number of case studies to illustrate the physical and information theoretic implications of embodiment. The case studies have been chosen from different domains — locomotion, grasping, and visual perception — to demonstrate the broad import of the concept of embodiment. Then we will deal with the extension of the concepts toward cognition. Finally, we will attempt to integrate the diverse case studies into a general overarching scheme that captures the essence of embodiment and morphological computation, and conclude.

Locomotion Case Studies

The fact that moving from one place to another, or locomotion, requires a body, comes as no surprise. However, it has been treated predominantly as a control problem by many; the body playing the part of a mere tool that has to be commanded appropriately. In this section, we will try to illustrate the contrary: shaping the body morphology and thereby the dynamics that result from the interaction with the environment can lead to stable and efficient locomotion, requiring very little control. We will illustrate these physical implications of being embodied on several machines and animals that walk or run. After that, a case study on leg coordination in insect walking will elucidate the impact of embodiment on information or control processes.

Physical Implications of Embodiment in Locomotion

In this section, we want to demonstrate that the body and its dynamics in the interaction with the environment, not control, are the key determinants of locomotion behavior. First, the passive dynamic walkers — brain-less machines — will serve as a powerful illustration of this concept. Second, we will present case studies that extend this idea to powered and controlled machines. However, the goal of the brain (or controller) is not to override, but to exploit the underlying body-environment dynamics and only tune it or channel it in desired directions. We will demonstrate how such an approach leads to greater stability and energy efficiency.

Passive dynamic walking. The passive dynamic walker, which goes back to McGeer (1990), is capable of walking down an incline without any actuation and without control. In other words, there are no motors, no sensors, and there is no microprocessor on the robot; it is brainless, so to speak. Its locomotion is an outcome of the slope of the incline (gravity is the only power source), and the mechanical parameters of the walker (mainly leg segment lengths, mass distribution, and foot shape). The original walker had four legs to provide stability in the lateral direction; Collins et al. (2001) have constructed a two-legged version which balances by using a counter-swing of the arms that are attached rigidly to their opposing legs (see Fig. 1, A).

As the passive dynamic walkers demonstrate, locomotion can be realized through pure, but carefully tuned mechanics only. However, the 'ecological niche' (i.e. the environment in which the robot is capable of operating) is extremely narrow: it only consists of inclines of certain angles. Therefore, the next objective is to extend this concept to machines with some practical capability — that can actively walk on level ground (or even uphill) and that can cope with rough terrain.

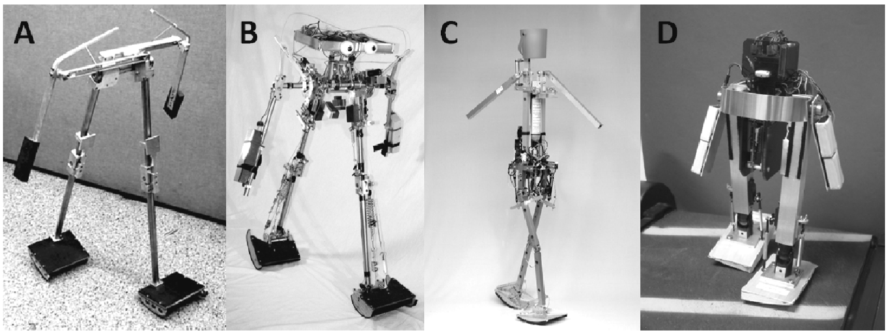

Fig. 1. Passive dynamic and passive dynamic based walkers. (A) The Cornell passive dynamic walker. It walks completely passively down an incline (Collins et al., 2005). (B)-(D) Passive dynamic based walkers are an extension of passive dynamic walkers. Actuation is added, such that they can walk on flat ground , but the energy-efficiency thanks to the exploitation of passive dynamics is preserved (Collins et al., 2005). (B) is an actuated extension of the passive walker (A).

Passive dynamic based walkers. These machines (Collins et al., 2005; Fig. 1, B-D) are a direct extension of the passive dynamic walking concept. Gravity (in the form of the incline) is substituted by small power sources. The robots can thus walk on level ground. However, they strive to preserve the advantages present in the entirely passive solution: minimal control and superior energy efficiency. The former goal can be illustrated on the Delft and Cornell bipeds that walk with simple control algorithms. Their only sensors detect ground contact, and their only motor commands are on/off signals issued once per step. The latter goal — superior energy efficiency — was also accomplished, as the cost of transport estimates testify[2].

What is the reason for the unprecedented energy efficiency of the passive dynamic based walkers? It is a consequence of the careful design of the body and of the minimalistic control scheme that only 'piggybacks' onto the underlying body dynamics. As is well known in physics, energy transfer is maximum at resonant modes of a system. The passive dynamic walkers and their active descendants contain a number of elements with pendulum-like dynamics: (1) a simple pendulum corresponds to the passive swing of the leg forward; (2) an inverted pendulum describes the motion of the hip mass over the stance leg; (3) another inverted pendulum characterizes the lateral rocking motion of the walker. The step frequency, stride length, and speed of the robots that can be observed are a direct consequence of the natural dynamics (the pendulums operating at their eigenfrequencies) that are exploited by the controller.[3]

The passive dynamic based walkers not only pave the way for energy-efficient robots of the future, but they also serve as models of human walking. The Cornell and Delft bipeds use anthropomorphic geometry and mass distributions in their legs and demonstrate ankle push-off and powered leg swinging, both present in human walking. They walk with human-like motion and human-like efficiency (Collins et al., 2005). The ease of altering different parameters and observing their effects helps us to better understand human walking.

Self-stabilization. Passive dynamic walkers have shown that locomotion can be realized through pure, but carefully tuned mechanics. However, how stable or adaptive is such a solution? In other words, how does a brainless machine cope with different slopes or with disturbances? The theory of nonlinear dynamical systems is often employed to analyze the phenomena involved in the mechanical (and also neural) aspects of locomotion. The walker is an example of a nonlinear dynamical system and walking patterns (which are periodic motions) correspond to limit cycles. Limit cycles in a nonlinear system can display attractive behavior, i.e. nearby trajectories are 'pulled' toward the limit cycle.

Mechanical self-stability, i.e. robustness to disturbances through local attractivity of the mechanical system, has been shown in a physical (McGeer, 1990) and mathematical (Coleman et al., 1997) walking model. In hopping or running, the dynamics is even more prolific. Fig. 2 illus-

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[2] The dimensionless mechanical specific cost of transport, c_{mt} = (positive mechanical work of actuators)/(weight * distance travelled), was 0.055 for the Cornell biped, 0.08 for its Delft colleague, which is similar to the value estimated for humans (0.05), but vastly outperforms the estimated value for the state-of-the-art Honda humanoid Asimo (1.6) (Collins et al., 2005).

[3] The problem of a controller, in this case a central pattern generator, adapting to the resonant frequencies of a walking machine has been addressed by Buchli & Ijspeert, 2008 and Verdaasdonk et al., 2006.

trates this phenomenon schematically. A monopod hopper driven by an open-loop controller compensates for disturbances without any explicit feedback mechanism, that is, without measuring the disturbances or altering the system. Self-stabilization has been investigated in a monopod (Ringrose, 1997), or quadruped (Poulakakis et al., 2006; Ringrose, 1997), for instance. Kubow & Full (1999) designed a dynamic model of a hexapedal runner and observed the recovery from rotational, lateral, and fore-aft velocity perturbations. Perturbations altered the translation and/or rotation of the body that consequently provided mechanical feedback by altering leg moment arms. Koditschek et al. (2004) provide an excellent review of the mechanical aspects of legged locomotion, analyzing cockroaches in particular and showing how this inspired the construction of the RHex robot — a robot with unprecedented mobility (Saranli et al., 2001). These studies show that running on rough terrain can be accomplished with simple feed-forward control in concert with a mechanical system that stabilizes passively. In the biological realm, the intrinsic properties of muscles further aid self-stability (Blickhan et al., 2007) and further assist in making the neural contribution to locomotion control simpler.

Body dynamics vs. control. This confrontation is already expressed in McGeer's original paper (McGeer, 1990). The passive dynamic walker has nothing but (passive body) dynamics. On the other end of the spectrum are traditional robots with strong emphasis on control. The Honda humanoid Asimo often serves as a representative of state-of-the-art of this approach to robot locomotion. We identify the following characteristics: (1) joint trajectories are planned and enforced rather than negotiated in interaction with the environment; (2) stabilization is achieved actively (through the famous zero-moment point control scheme: Vukobratovic & Vorovac, 2004) rather than passively; (3) stiff, high-power, and high-frequency actuation is used. As a consequence of these characteristics, both computational and energetic requirements are high. On the other hand, the robot is very versatile — it can move its limbs into every possible position, it can walk uphill, downhill, even up and down the stairs.

By contrast, all the passive dynamic walker can do is walk, and it can only walk down an incline. Nevertheless, the descendants of the passive dynamics exploitation approach, the passive dynamic based walkers (Collins et al., 2005) or RHex (Saranli et al., 2001), demonstrate that the narrow ecological niche can be gradually expanded, while preserving the merits of this approach.

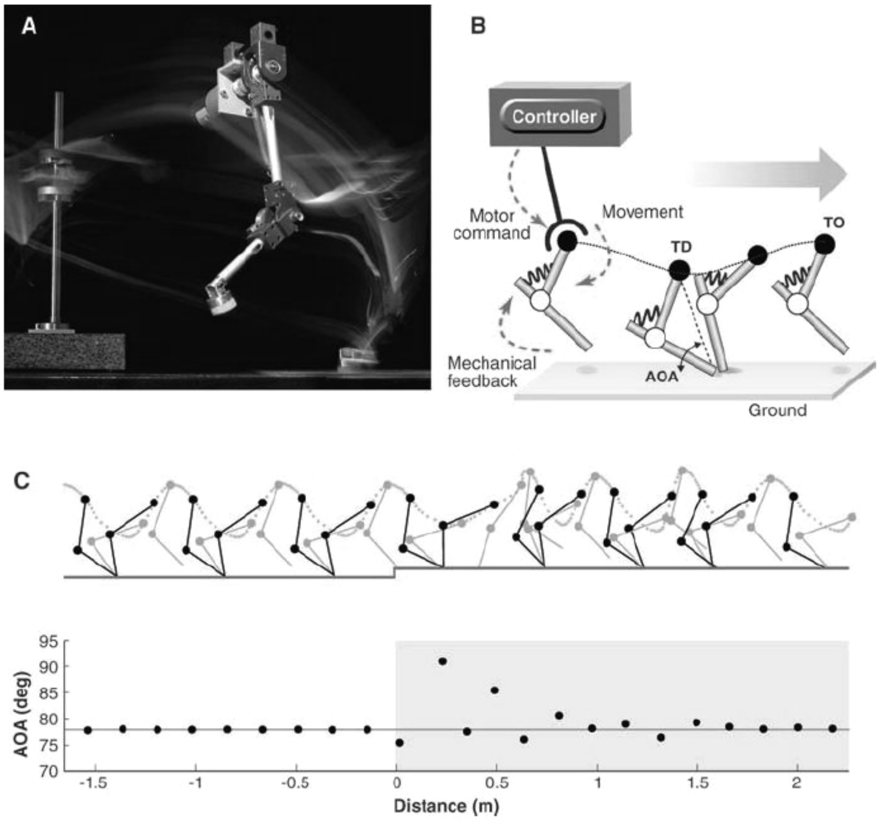

Fig. 2. Self-stabilization. Adaptivity is part of the mechanical structure itself. (A) Picture of a two-dimensional underactuated monoped hopping robot attached to a central rod with a rotational joint (courtesy of A. Seyfarth and A. Karguth). (B) A schematic representation of the hopping robot in the different phases of locomotion: flight, touchdown (TD) [with angle of attack (AOA)], and takeoff (TO). Only the joint depicted by the black circle (hip joint) is actuated, the knee (white circle) is passive, and the lower limb is attached to the upper limb with a simple spring. (C) Output of a simulation of the robot. The upper part of the panel shows the trajectory of the model over time as a sequence of stick figures; in the lower part, the angle of attack (the angle at which the leg hits the ground) is plotted. The model exhibits a stable hopping gait with a periodic hip motor oscillation, as indicated by the constant AOA at every step in the left side of the panel. At distance d = 0 m, there is a step in the ground that disturbs the robot's movement but to which the robot adapts without the need for any changes in the control. This purely mechanical phenomenon is called self-stabilization (Figure from Pfeifer et al., 2007; there adapted from Blickhan et al., 2007).

Information Theoretic Implications of Embodiment in Locomotion

The view presented in the previous section overly polarizes the situation. Body and brain should not be viewed as competitors, but rather collaborators. The tasks can be distributed and accomplished by the substrate that is more appropriate. What we have demonstrated so far is that in many locomotion-related tasks, the body itself is the candidate of choice. Nevertheless, for versatile locomotion, control is indispensable. Traditionally, control algorithms need to be fed with information about the state of the system, as obtained from sensors. Based on that, a decision, regarding the leg coordination for instance, is taken centrally. However, there are alternatives to the centralized control paradigm, which take embodiment into account. What we want to elucidate in this section is that embodiment is as important for the physical processes as it is for the informational processes. The inputs to a control scheme necessarily come through the body dynamics (see Iida & Pfeifer, 2006, for an account on sensing through body dynamics in a dynamic quadruped robot). The following case study illustrates how the body and interaction with the environment can replace a central communication between legs in insect walking.

Leg Coordination in Insect Walking[4]. Leg movements in insects are controlled by largely independent local neural circuits that are connected to their neighbors. There is no central controller that coordinates the legs during walking. The leg coordination comes about by the exploitation of the interaction with the environment (Cruse, 1990; Cruse et al., 2002). If the insect stands on the ground and moves forward by pushing backwards with one of its legs, as an unavoidable implication of being embodied, all the joint angles of the legs standing on the ground will instantaneously change. The insect's body is pushed forward, and consequently the other legs are also pulled forward and the joints will be bent or stretched. This fact can be exploited to the animal's advantage. All that is needed is angle sensors in the joints — and they do exist — for measuring the change, and there is global communication between the legs! But the communication is through the interaction of the agent with the environment, not through neural processing.

Inspired by the fact that the local neural leg controllers need only exploit this global communication, a neural network architecture called WalkNet has been developed which is capable of controlling a six-legged robot (Dur et al., 2003). This instance of morphological computation takes over part of the task that would have to be done by the brain — the communication between the legs and the calculation of the angles on all the joints — is performed by the interaction between the insect and the world.

[4] This case study has previously appeared in Pfeifer & Gomez, 2009.

Grasping Case Studies

At first sight, grasping and locomotion do not seem to have much in common. However, as we will show in this section, the implications of embodiment illustrated thus far in locomotion can be equally well demonstrated in case studies that involve grasping. In essence, the rich and dynamic interactions of walking or running bodies with the ground will be replaced by equally complex interactions of hand morphologies and objects being grasped.

Physical Implications of Embodiment in Grasping

In this section, we discuss how morphology and materials contribute to grasping behavior. Hand joint structure, muscle mechanics, and the distribution and density of bone to joint movements and muscle recruitment during manipulative behavior are all important variables, as investigated by Marzke & Marzke (2000). It has also been reported that ridged structure of human skin offers better grip due to increased friction (Cartmill, 1979). However, we will use two robotic case studies for our illustration of 'cheap grasping', i.e. grasping that is stable and reliable, yet requires little control. First, we will demonstrate a robotic hand, in which the attention paid to the mechanical construction leads to self-adaptation of the grasp to different objects. Second, we will present a recent universal robotic gripper, where the morphological approach was taken to its extreme.

Cheap Grasping with a Robotic Hand[5]. The 18 degrees-of-freedom (DOF) tendon driven 'Yokoi hand' (Yokoi et al., 2004; Fig. 3) which can be used as a robotic and a prosthetic hand, is partly built from elastic, flexible, and deformable materials (this hand comes in many versions with different materials, morphologies, sensors, etc.; here we only describe one of them). The tendons are elastic, the fingertips are deformable and between the fingers there is also deformable material.

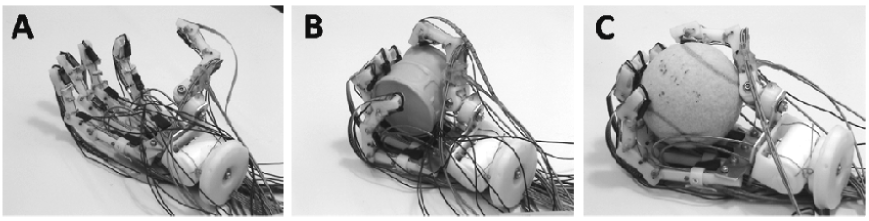

Fig. 3: 'Cheap' grasping with a robotic hand: exploiting system-environment interaction. (A) The Yokoi hand exploits deformable and flexible materials to achieve self-adaptation through the interaction between environment and materials. (B)-(C) Final grasp of different objects. The control is the same, but the behavior is very different.

[5] This case study has previously appeared in Pfeifer & Gomez, 2009.

When the hand is closed, the fingers will, because of the anthropomorphic morphology, automatically come together. For grasping an object, a simple control scheme, a 'close' is applied. Because of the morphology of the hand, the elastic tendons, and the deformable fingertips, the hand will automatically self-adapt to the object it is grasping.

Cheap grasping with a universal gripper. As our everyday experience confirms, a multifingered hand is an extremely dexterous manipulator. However, from a robotic perspective, this approach is highly complex from a hardware as well as software point of view. Brown et al. (2010) have therefore devised a gripper that utilizes a completely different strategy. Individual fingers are replaced by a single mass of granular material (e.g., ground coffee). The principle of operation is illustrated in Fig. 4, D. The 'bag' containing granular material is pressed onto an object, flows around it, and conforms to its shape. Then, a vacuum pump is used to evacuate air from the gripper, which makes the granular material jam and stabilize the grasp. The gripper conforms to arbitrary shapes passively, that is without any sensory feedback, thanks to its morphological properties only. Brown et al. identify three mechanism that contribute to the gripping: (i) geometric constraints from interlocking between gripper and object surfaces; (ii) static friction from normal stresses at contact; and (iii) an additional suction effect, if the gripper membrane can seal off a portion of the object's surface. The properties of the gripper can be changed by using a different granular material. Objects of various shapes (see Fig. 4, E) as well as hardness (from steel springs to raw eggs) can be gripped. An additional advantage is that the orientation of objects that are picked up and placed again does not change.

In the two case studies presented, there is no need for the agent to 'know' beforehand what the shape of the to-be-grasped object will be (which is normally the case in robotics, where the contact points are calculated before the grasping action: Molina-Vilaplana et al., 2007). In the first study, the shape adaptation is taken over by the morphology of the hand, the elasticity of the tendons, and the deformability of the fingertips, as the hand interacts with the shape of the object. In the second study, the physical properties of the granular material and how they change when air is evacuated play a key part. In both cases, control of grasping is very simple, or, in other words, very little 'brain power' is required. Clearly, these designs have their limitations; for fine manipulation more sophisticated sensing, actuation, and control may be required (Borst et al., 2002). However, a powerful fundament on which the next layers can rest has been provided.

For prosthetics, there is an interesting implication. EMG signals can be used to interface the robot hand non-invasively to a patient: even though the hand has been amputated, he or she can still intentionally produce muscle innervations which can be picked up on the surface of the skin by EMG electrodes. If EMG signals, which are known to be very noisy, are used to steer the movement of the hand, control cannot be very precise and sophisticated. But by exploiting the self-regulatory properties of the hand, there is no need for very precise control, at least for some kinds of grasping: the relatively poor EMG signals are sufficient for the basic movements (Hernandez Arieta et al., 2006; Yu et al., 2006).

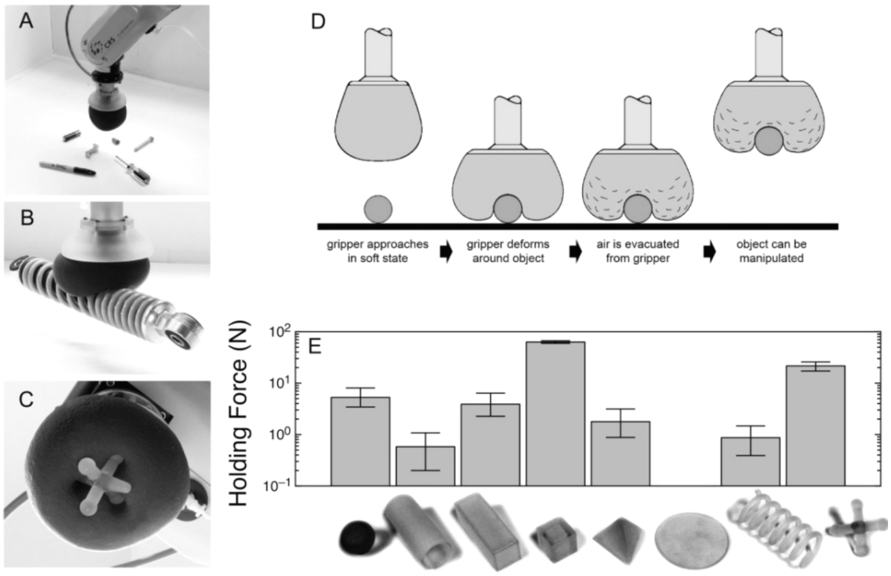

Fig. 4. Jamming-based grippers for picking up a wide range of objects without the need for active feedback. (A) Attached to a fixed-base robot arm. (B) Picking up a shock absorber coil. (C) View from the underside. (D) Schematic of operation. (E) Holding force Fh for several three-dimensional-printed test shapes (the diameter of the sphere shown on the very left, 2r = 25.4 mm, can be used for size comparison). The thin disk could not be picked up at all (from Brown et al., 2010, courtesy John Amend of Cornell University).

Information Theoretic Implications of Embodiment in Grasping

As we have seen, and similarly to the locomotion case, morphology and material properties can take over a significant part of a grasping task. However, in more complex scenarios, mechanical 'intelligence' has to be aided by software or control. In order for a controller to be able to take the right decisions and issue proper motor commands, it needs to perceive the relevant information regarding the agent's interaction with the environment. Our goal in this section is to emphasize that the body morphology is as important for the perception task, as it is for taking actions. We have picked slippage sensing for our case study — a prerequisite for stable grasping and fine object manipulation — and we will show how the particular shape and material properties of an artificial skin can facilitate perception.

Slippage detection. In humans, the ridged skin structure not only improves the mechanics of grasping as mentioned above, but also magnifies the pressure (which can be perceived) exerted by the manipulated object (Fearing & Hollerbach, 1984), and acts as a frequency filter for specific skin mechanoreceptors (Scheibert et al., 2009). Similar properties are desirable in robotic or prosthetic hands. A wide range of tactile sensors have been developed for slippage detection which use different transduction principles: piezoelectric sensors sensitive to vibrations, skin with round ridges and strain sensors, vibrating nibs on the skin surface sensed by accelerometers, or brushes on top of capacitive membranes (see the references in Damian et al., 2010). The morphology and material properties are significantly involved in all of those designs. In what follows, we want to look in detail into yet another solution where morphology maximizes the information that can be acquired about a slippage event.

Damian et al. (2010) devised a tactile sensor consisting of a silicone skin layer with ridges a few millimeters apart which transduces surface events to a force sensing resistor beneath (Fig. 5, A). Whereas a flat skin

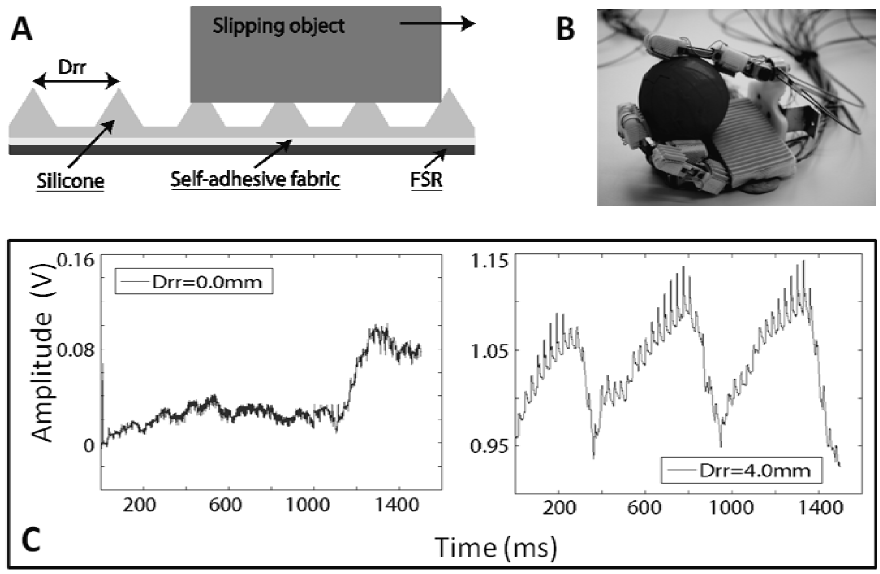

Fig. 5: Slippage detection through ridged skin. (A) Schematics of the artificial skin. Silicone skin with evenly spaced ridges is glued over a Force Sensing Resistor (FSR). (B) Robotic hand equipped with artificial ridged skin. (C) Signal generated by an object sliding over a skin without ridges (left), and with ridges 4 mm apart (right). The ridged skin provides a stronger signal with higher amplitude. In addition a clear periodic pattern allows for detection of slippage speed. (Damian et al., 2010)

without ridges, which was used as a reference, fails to detect an object sliding over it, ridged skin gives rise to peaks in the pressure sensor readings. Moreover, the frequency of the pressure signal obtained is directly proportional to the slippage speed and inversely proportional to the distance between ridges. The inter-ridge distance itself was found to further influence the quality of frequency encoded information. Among all skins, the one with a 4 mm spacing between ridges yielded discriminatory peak frequencies for each velocity (Fig. 5, C). The skin was afterwards employed in a robotic hand to stabilize grip. In summary, in this study, much of the electronic and algorithmic complexity present in other tactile sensing approaches has been successfully off-loaded to the morphology and allowed to detect slippage and gauge its speed with theoretically a single force sensor.

Visual Perception Case Studies

Unlike walking or grasping, seeing seems to be concerned exclusively with perception rather than action. The goal is to acquire useful information from the environment that can be used to perform various tasks. Nevertheless, embodiment plays a key role in the information that can be acquired and such information theoretic implications of embodiment for visual perception will be the topic of this section.

A prominent theory of visual perception was proposed by David Marr (1982): vision was treated as a stage-like computational process proceeding from a two-dimensional visual array (retina/camera image) to a three-dimensional description of the world as output. Whereas this approach has lead to many successes in computer vision, robots still fall short of the capabilities that humans and animals demonstrate in object recognition, identification, and scene understanding in unstructured environments.

An alternative, and perhaps a remedy to the shortcomings of the treatment of visual perception as image processing, can be provided by embodiment. The scope of the investigation of visual perception has to be broadened to the generation of raw input image. The amount of information present in the input flow is shaped by two factors: (1) morphology of the sensory apparatus; and (2) active generation of information through sensory-motor coordination. We will address these factors separately in the sections below, but we want to stress that they always act concurrently.

Thus far, we have been referring to the information theoretic implications of embodiment in a mostly informal sense. However, the information content or structure present in the sensory and motor modalities can be quantified. Lungarella & Sporns (2006) presented several methods for measuring the (undirected) information present in sensory modalities

(Shannon entropy, mutual information, integration, and complexity). To extract directed, or causal, relationships, such as from sensors to motors or vice versa, they employed transfer entropy; however, other measures are also available, as analyzed in Lungarella et al., 2007). Polani and colleagues have devised a different measure, empowerment, which measures how much influence an agent has on its environment, but only that influence that can be sensed by the agent's own sensors (see e.g., Jung et al., 2011). Yet another embodiment quantification method was presented recently by Thornton (2010), testifying the recent attention given to this subject. One of his case studies features a passive dynamic walker that we have (less formally) analyzed in the section on locomotion. Although such analysis tools are equally suited for animals and robots engaged in behavior, robots, as we have already discussed, are significantly easier to monitor and manipulate. Following the synthetic modeling approach, we will thus emphasize case studies on robots.

The Role of Eye Morphology in Visual Perception

Human eye. The retina of a human eye is a variable resolution sensor: the distribution of photoreceptors is non-homogeneous. The density of cones, which are used for high acuity vision, is greatest in the center (fovea) (e.g., Curcio et al., 1990). Through this morphological arrangement, a limited number of sensing and processing elements can provide both high acuity in the center of the visual field, and a wide field of view. In robots, the retinal morphology can be emulated by the log-polar transformation (e.g., Sandini & Metta, 2002), and the degree of variable resolution can be scaled arbitrarily. Martinez et al. (2010a) investigated this effect in a robot with two eyes performing vergence behavior (simultaneous movement of both eyes in opposite directions to obtain single binocular vision). The sensor morphology as represented by the log-polar transform clearly manifests itself in the information structure calculated on a sequence of images obtained from the robot. A similar phenomenon was observed by Lungarella & Sporns (2006). There, a simulated wheeled robot (but with a human-inspired eye) was driving around colored objects and foveated on them.

Insect eye[6]. It has been shown that for many objectives (e.g. obstacle avoidance) motion detection is all that is required. Motion detection can often be simplified if the light-sensitive cells are not spaced evenly, but if there is a non-homogeneous arrangement. For instance, Franceschini and co-workers (1992) found that in the compound eye of the house fly the spacing of the facets is denser toward the front of the animal. This non-homogeneous arrangement, in a sense, compensates for the phenomenon

[6] This case study has been adapted from Pfeifer & Gomez, 2009.

of motion parallax, i.e. the fact that at constant speed, objects on the side travel faster across the visual field than objects towards the front: it performs the 'morphological computation', so to speak. Allowing for some idealization, this implies that under the condition of straight flight, the same motion detection circuitry — the elementary motion detectors, or EMDs — can be employed for motion detection for the entire eye, a principle that has also been applied to the construction of navigating robots (e.g., Hoshino et al., 2000). In experiments with artificial evolution on real robots, it has been shown that certain aims, e.g. keeping a constant lateral distance to an obstacle, can be solved by proper morphological arrangement of the ommatidia, i.e. denser frontally than laterally without changing anything inside the neural controller (Lichtensteiger, 2004; Fig. 6). Because the sensory stimulation is only induced when the robot (or the insect) moves in a particular way, this is also called information self-structuring (or more precisely, self-structuring of the sensory stimulation), which leads us to the next section.

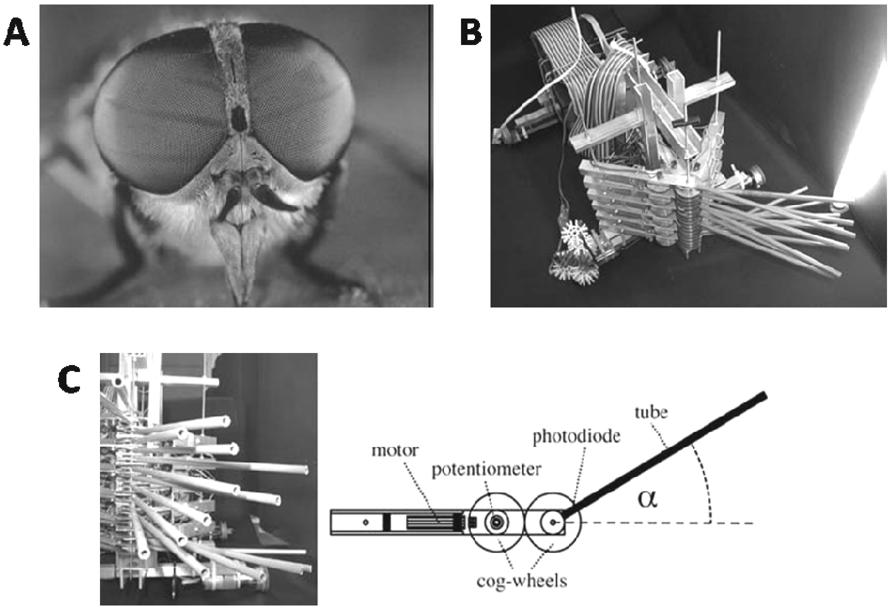

Fig. 6. Morphological computation through sensor morphology — the Eyebot. The specific non-homogeneous arrangement of the facets compensates for motion parallax, thereby facilitating neural processing. (A) Insect eye. (B) Picture of the Eyebot. (C) Front view: the Eyebot consists of a chassis, an on-board controller, and sixteen independently-controllable facet units, which are all mounted on a common vertical axis. A schematic drawing of the facet is shown on the right. Each facet unit consists of a motor, a potentiometer, two cog-wheels and a thin tube containing a sensor (a photo diode) at the inner end. These tubes are the primitive equivalent of the facets.

Active Vision

The previous section has demonstrated how a particular sensor morphology affects the information structure of the raw data that reaches the sensor and that enters subsequent processing afterwards. However, the sensory stimulation is not passively received, but rather actively generated. The point we want to make was beautifully expressed by John Dewey already in 1896 (Dewey, 1896):

> We begin not with a sensory stimulus, but with a sensory-motor coordination […] In a certain sense it is the movement which is primary, and the sensation which is secondary, the movement of the body, head, and eye muscles determining the quality of what is experienced. In other words, the real beginning is with the act of seeing; it is looking, and not a sensation of light.

Only much later was Dewey's visionary observation picked up by research in active perception (e.g. Bajcsy, 1988; Churchland et al., 1994; Gibson, 1979; Noe, 2004).

Again, we will pick a robotic case study to illustrate this point. Lungarella & Sporns (2006) used an upper torso humanoid robot (Fig. 7, A) to evaluate the contribution of sensory-motor coupling to different informational measures by comparing two experimental conditions. In both conditions, the robot arm was following a preprogrammed trajectory. The movement of the ball results in a displacement of the ball relative to the head and leads to physical stimulation in the head-mounted camera. In the first condition, which we will refer to as 'fov', the sensory feedback is exploited by the controller of the robot head with camera to track the end-effector (orange ball). In other words, the sensory-motor loop (Fig. 7, B) was ensuring the orange ball stays at the center of the visual field — the fovea. In the second condition, 'rnd', the movement of the camera is unrelated to the movement of the ball (sensory-motor coupling is disrupted). The amount of information in the sequence of camera images was measured for both conditions (Fig. 7, C). As can be seen, there is more information structure in the case of the foveation condition for all measures; for example, the dark region in the center of the entropy panel indicates that entropy is clearly diminished in the center of the visual field (disorder has been reduced, or in other words, information structure has been induced), which is due to foveation being a sensory-motor coordinated behavior. Similar results were reported by Martinez et al. (2010a), who used a head with two cameras. In their case, coordinated behavior consisted in vergence, i.e. both eyes tracking salient objects. Moreover, Martinez et al. (2010a) also showed that it is not arbitrary coordinated behavior that generates information structure. A different behavior, one eye tracking the object and the other following its movements, i.e. without vergence, did not generate more information structure than random behavior. Although this behavior may seem sensory-motor coordinated to the outside observer, it does not match the robot's morphology, in this case the sensory apparatus. This illustrates the point that morphology and active perception cannot be considered in isolation.

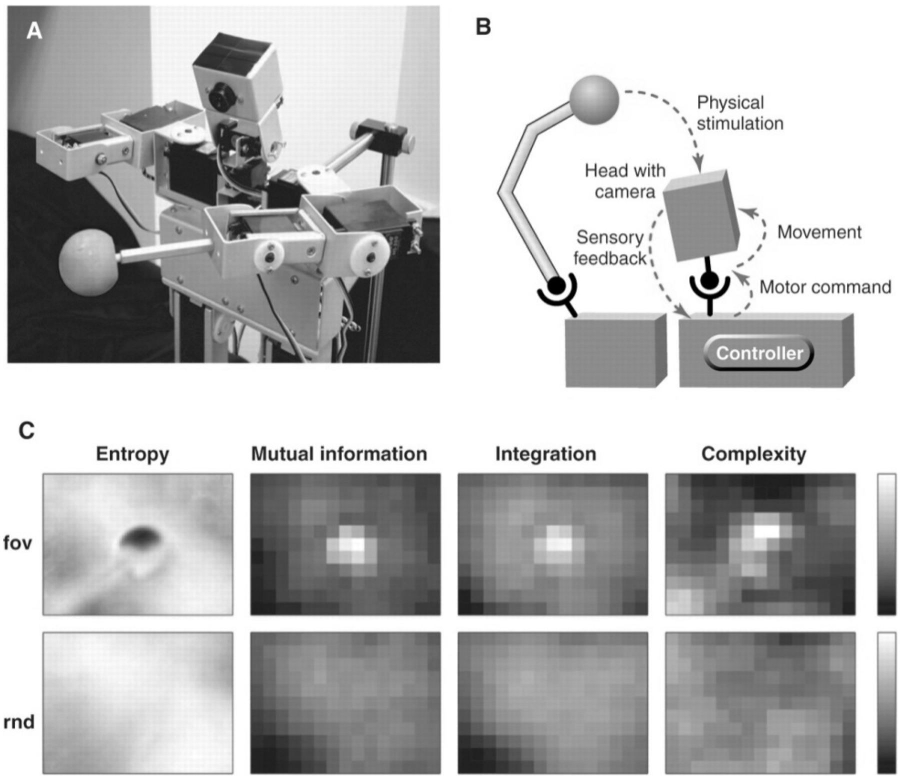

Fig. 7. Information self-structuring. (A) Picture of the robot, a small humanoid with a pan-tilt head equipped with a camera. (B) Schematic representation of the experimental setup. (C) Various measures to capture information structure: entropy (the amount of disorder in the system), mutual information (the extent to which the activity of one pixel can be predicted from the combined activities of neighboring pixels), integration (a measure of global coherence), and complexity (a measure that captures global coherence and local variation). The measures are applied to the camera image in the case of the foveation condition (top) and random condition (bottom). (From Pfeifer et al., 2007; there adapted from Lungarella & Sporns, 2006)

Information structure in individual sensory modalities, such as in the visual modality as shown above, is definitely a prerequisite for subsequent processing. However, for effective control of behavior we are also interested in relations between modalities, and in relations in time. In particular, we are interested in directed relations in time, such as the ones between motor and sensory modalities, which may indicate causal relations. Sensory-motor coordinated behavior increases the directed information flow, as measured using transfer entropy (Lungarella & Sporns, 2006; Martinez et al., 2010b). Such relations can be further exploited by the agent to learn to predict the consequences of its behavior. Moreover, predictability in the sensory-motor loop can be used to drive development (e.g., Oudeyer et al., 2007). Learning and representing the relations that exist between sensory and motor modalities constitute the first traces of cognition and will be the subject of the next section.

From Sensory-motor Interaction to Embodied Cognition

Thus far, we have been dealing with relatively low-level tasks such as locomotion, grasping, or simple visual perception. We have shown that such tasks can be performed without sophisticated cognitive processing, but rather through exploitation of body dynamics and interaction with the environment. While this research is interesting in itself, how does it relate to higher-level cognition? We will provide the link in this section.

Embodied Categorization[7]

For an autonomous embodied agent acting in the real world (e.g., an animal, a human, or a robot), perceptual categorization — the ability to make distinctions — is a hard problem (Harnad, 2005). First, based on the stimulation impinging on its sensory arrays (sensation) the agent has to rapidly determine and attend to what needs to be categorized. Second, the appearance and properties of objects or events in the environment being classified fluctuate continuously, for example owing to occlusions, or changes of distances and orientations with respect to the agent. And third, the environmental conditions (e.g., illumination, viewpoint, and background noise) vary considerably. There is much relevant work in computer vision that has been devoted to extracting scale- and translation-invariant low-level visual features and high-level multidimensional representations for the purpose of robust perceptual categorization (Riesenhuber & Poggio, 2002). Following this approach, however, categorization often turns out to be a very difficult if not an impossible computational feat, especially when sufficiently detailed information is lacking.

A solution that can only be pursued by embodied agents — but is not available when using a purely disembodied (i.e., computational) approach — is that through their interaction with the environment, agents generate the sensory stimulation required to perform the proper categorization and thus drastically simplify the problem of mapping sensory stimulation onto perceptual categories. The most typical and effective way is through a process of sensory-motor coordination. One demonstration of how sensory-motor coordination influences category formation

7 This section has been adapted from Pfeifer et al., 2008.

can be found in the experiments by Pfeifer & Scheier (1997). These experiments show that mobile robots can reliably categorize big and small wooden cylinders only if their behavior is sensory-motor coordinated. A similar point is illustrated by the artificial evolution experiments of Beer (2003), where a simulated agent learns to discriminate between circular and diamond-shaped objects, or Nolfi (2002). The fittest agents, that is, those that most reliably categorized different kind of objects, were those engaging in sensory-motor coordinated behavior. Intuitively, in these examples, the interaction with the environment (a physical process) creates additional (i.e., previously absent) sensory stimulation, which is highly structured, thus facilitating subsequent information processing.

Let us compare the categories that we have just come across with categories as symbols as we know them from classical symbolic AI. Taking Beer's case study, if it was realized in a symbolic architecture, we should find a 'diamond' symbol, which represents the diamonds and onto which the instances of diamonds in the real world need to be mapped (a nontrivial task, as described above). Moreover, the pitfall of this approach is that cognitive processing becomes detached from real world interaction and from meaning for the agent (the notorious symbol grounding problem: Harnad, 1990). On the other hand, when one examines the control architectures used by Pfeifer & Scheier (1997) or by Beer (2003), it is not possible to identify a site where the categories (big vs. small cylinders, or circles vs. diamonds) reside. Beer's dynamical systems analysis of the behaving agent does not reveal clear neural correlates of 'circles' or 'diamonds' either. Rather than corresponding to 'labels' defined from the outside, the categories are in fact behaviors. A small cylinder can be grasped, whereas a big one cannot; a circle is caught by the agent, whereas a diamond is avoided. Thus, categories are intrinsically meaningful to the agent and they are emergent from complex system-environment dynamics (see also Kuniyoshi et al., 2004).

On the other hand, it is probably fair to say that the discrimination tasks the agents were engaged in were of limited complexity. The opponents therefore rightly raise the question of scalability (e.g., Edelman, 2003) and argue that clearly identifiable representations allowing for hierarchical abstractions are necessary to tackle more complex scenarios. However, the dynamical systems framework and the concept of attractors that we have witnessed in the section dealing with stability in locomotion can provide a solution here. Kuniyoshi et al. (2004) or Pfeifer & Bongard (2007, ch.5), explain how, adopting the dynamical systems perspective, discretely identifiable states emerge as attractors in the combined physical and neural system of an agent. For instance, such symbols (or proto-symbols) could be gaits in a running quadruped, or they can be 'categorizing behaviors'. On top of these proto-symbols, further, more cognitive but still grounded, processing can take place.[8]

Body Schema and Forward Models

As we have seen in the previous section, the distinction between cognitive and sensory-motor starts to blur. Categorization, perception, but even memory processes turn out to be directly coupled to sensory-motor processes and thus to embodiment (e.g., Edelman, 1987; Glenberg, 1997; Pfeifer & Scheier, 1999). What is the natural way in which an agent interacting with the world can gradually acquire cognition? We propose to follow a bottom-up and developmental pathway. Rather than starting from representations of objects or the world around the agent, we propose to start representing the very basis: the agent's body and its low-level interaction with the environment. In other words, as we have argued, any cognitive processing will always be mediated by the body and the sensory-motor loops. Therefore, these are the first candidates for an agent to learn about.

Concepts that are currently being studied, mainly in neuroscience and psychology, are 'body schema' (e.g., De Preester & Knockaert, 2005; Haggard & Wolpert, 2005; Higuchi et al., 2006; Maravita et al., 2003) and 'forward', or internal, models (Bays & Wolpert, 2007; Webb, 2004; Wolpert et al., 1998). Both concepts have also direct relevance for robotics (see e.g., Hoffmann et al., 2010, for a review). The body schema can be viewed as the sensory-motor 'representation' of the agent's body and its action possibilities. Forward models enable agents to predict the consequences of their actions and are related to anticipatory behavior (e.g., Pezzulo, 2007). In more concrete terms, for instance, in the (uncertain, dynamic, potentially hostile) world out there, it may be of advantage to: (i) predict the next sensory feedback in advance — for instance, during rapid locomotion, biological feedback is too slow; (ii) distinguish self-generated sensory information from sensory input generated by the environment, leading to detection of changes in the environment[9]; or (iii) simulate different courses of action and choose the one with the best consequences. Whereas it is not surprising that humans possess such capabilities, they have been discovered even in much simpler animals. For instance, prediction is demonstrated in the motor preparation of the prey-catching behavior of the jumping spider (Schomaker, 2004). As another example, rats are able to compare alternative paths in a T-maze before actually acting, thus 'planning in simulation' (Hesslow, 2002).

As discussed by Clark & Grush (1999), forward models are the

[8] Maass et al., 2004 provide a neurally inspired computational model of a two-tiered architecture that could be used to implement such a processing hierarchy.

[9] For instance, it feels different when we move our eyes than when the world moves, although on the retina it may look the same.

simplest instances of circuitry that emulates the world outside and thus stands for something that is not currently present in the sensory and motor states. Thus, we may want to attribute representation to such circuitry. A 'decoupled' forward model that is not just a few steps ahead of the sensory-motor reality but that can be executed independently, in the brain only, can then be viewed as emulation/simulation of the interaction with the world, or world model. Interestingly, such a forward model can also be exploited to exercise embodied categorization, which we have presented in the previous section, in simulation. In other words, if the agent can predict the sensory consequences of its actions, it can also 'imagine' catching a circle or diamond, or grasping a cylinder. The outcome of such internal simulation can be used to derive a perceptual judgment that would otherwise not have been possible. This is demonstrated by the agent of H. Hoffmann (2007), which uses such a 'mental' rehearsal of driving in its environment to discriminate passages and dead ends.

Let us now wrap up the nature of representations and cognition that we are acquiring. Rather than representing static features (such as objects), dynamic interaction patterns, which involve the robot acting in the environment, are represented. Such representations are best viewed as motor-based. They are action-oriented, originate in the sensory-motor apparatus and remain intimately related with it (Clark & Grush, 1999; Pezzulo, 2007)[10]. Whether we want to call these phenomena 'cognitive' depends on our definition of cognition. Some views reject the cognitive/non-cognitive divide altogether, some include into the cognitive realm all kinds of adaptively valuable organism/ environment coupling (e.g., Thelen & Smith, 1994). While we consider these views equally legitimate, the view proposed by Clark & Grush (1999), among others, is that cognizers must display the capacity for environmentally decoupled thought and contemplation of options. This is exactly what a decoupled forward model provides: simulation of the world, or 'mental imagery'. This phenomenon is believed to be at the core of grounded cognition (Barsalou, 2008; Gallese & Lakoff, 2005).

Discussion and Conclusion

We have seen a large variety of case studies. The question that immediately arises is whether there are general overarching principles governing all of them. A recently published scheme (Pfeifer et al., 2007) shows a potential way of integrating all of these ideas.

We will use Fig. 8 to summarize the most important implications of embodiment and to embed our case studies into a theoretical context.

[10] As opposed to symbolic AI representations that are world-centered.

Driven by motor commands, the musculoskeletal system (mechanical system) of the agent acts on the external environment (task environment or ecological niche). The action leads to rapid mechanical feedback characterized by pressure on the bones, torques in the joints, and passive deformation of skin tissue. In parallel, external stimuli (pressure, temperature, and electromagnetic fields) and internal physical stimuli (forces and torques developed in the muscles and joint-supporting ligaments, as well as accelerations) impinge on the sensory receptors (sensory system). The patterns induced thus depend on the physical characteristics and morphology of the sensory systems and on the motor commands. Especially if the interaction is sensory-motor coordinated, as in foveation, reaching, or grasping movements, information structure is generated. The effect of the motor command strongly depends on the tunable morphological and material properties of the musculoskeletal system, where by tunable we mean that properties such as shape and compliance can be changed dynamically. All parts of this diagram are crucial for the agent to function properly, but only one part concerns the controller or the central nervous system. The rest can be seen as 'morphological computation'.

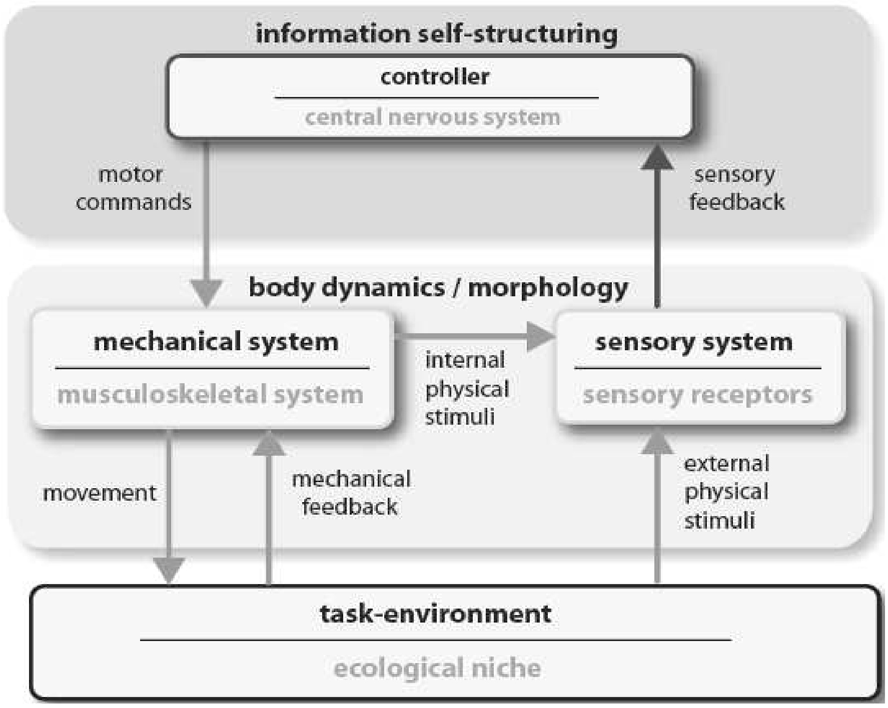

Fig. 8: Overview of the implications of embodiment — the interplay of information and physical processes (from Pfeifer et al., 2007; see text for details).

Let us now go through the case studies we have presented and locate them in Fig. 8. The passive dynamic walker is an instance of an interaction of the mechanical system with the environment solely — controller and sensory system are completely absent. Stabilization is achieved through the mechanical feedback loop shown in the lower left of the figure; in this case, the feedback is generated through ground reaction forces[11]. This scheme can be amended by a feed-forward controller that blindly sends motor commands to the mechanical system. That is the case for the monopod in Fig. 2 or for the hexapod RHex. As there is still no sensory system, these robots can function in the real world only thanks to mechanical self-stabilization. The 'cheap grasping' case studies illustrate a similar concept. This time, the material and morphology of the hand/gripper serve to stabilize a grasp without sensing. By contrast, the passive dynamic based walkers feature a complete scheme already — there is a sensory system and a feedback path to the controller. However, the control is rudimentary and it is still the intrinsic dynamics of the body that plays a dominant role. As a consequence of this — the intrinsic body dynamics is exploited rather than overridden — the robots also demonstrate unprecedented energy efficiency.

The study on leg coordination in insect walking provides a bridge from the physical implications of embodiment (that we have reviewed in the previous paragraph) to the information theoretic ones. Insects, when walking, also exploit mechanical feedback generated through ground reaction forces, but rather than exploiting it for gait stabilization, they capitalize on exploiting the internal sensory stimulation generated in the joint angles as one leg pushes back (thus inducing changes in the joint angles of all the other legs that are standing on the ground). This process corresponds to the lower left part of Fig. 8 and the arrow pointing from the mechanical system to the sensory system. This information can then be used for local control of individual legs. The study on slippage detection in grasping illustrates the role of the morphology of the sensory system. The particular shape of the skin — its surface is covered by ridges — magnifies the pressure exerted by objects that are grasped, and at the same time acts as a frequency filter, allowing for simply slippage speed calculation.

The case studies dealing with vision illustrate the effect of sensory morphology *and* sensory-motor coordination on the information structure that reaches a sensor. In the Eyebot, the 'insect eye' case study, given a certain behavioral pattern, e.g. moving straight, the robot induces sensory stimulation which has to be subsequently processed, for instance to achieve obstacle avoidance. The study shows that evolving a specific

[11] Note that the fact that the robot has no sensors and thus does not know anything about this mechanical feedback does not imply that there is no such feedback.

morphology of the facet distribution can take over a significant part of the 'processing', producing already highly structured and easy to process information for the nervous system. This process corresponds to the outer loop from the controller via mechanical system to task environment, back to sensory system and controller. The active vision case studies demonstrate the effect of action on the quality of subsequent perception, highlighting the need to treat perception as an intrinsically active process. We have also shown that the amount of sensory information can be measured quantitatively and that sensor morphology and sensory-motor coordination always go hand in hand and have to match.

There are two main conclusions that can be drawn from these case studies. First, it is important to exploit the dynamics in order to achieve energy-efficient and natural kinds of movements. The term 'natural' not only applies to biological systems, but artificial systems also have their intrinsic natural dynamics. Second, there is a kind of trade-off or balance: the better the exploitation of the dynamics, the simpler the control, the less neural processing will be required. Note that all this only works, if the agent is actually behaving in the real world and therefore is generating sensory stimulation. Once again, we see the importance of the motor system for the generation of sensory signals, or more generally for perception. It should also be noted that motor actions are physical processes, not computational ones, but they are computationally relevant, or put differently, relevant for neural processing, which is why we use the term 'morphological computation'.

Having said all this, it should be mentioned that there is an additional trade-off. The more the specific environmental conditions are exploited — and the passive dynamic walker is an extreme case — the more the agent's success will be contingent upon them. Thus, if we really want to achieve brain-like intelligence, the brain (or the controller) must have the ability to quickly switch to different kinds of exploitation schemes either neurally, or mechanically through morphological change.

Finally, we have sketched a pathway how cognition can naturally emerge on top of the low-level sensory-motor processes the body is engaged in. It is the body and the interaction with the environment that are the natural candidates for first primitive representations. We want to point out that cognition is in the service of behavior here. That is, these first representations or models have to bring behavioral advantage. We have shown how this is indeed the case in simple situations where a forward model can provide an estimate of the future consequences of an action. As these simple predictive mechanisms become progressively more decoupled and autonomous, and as perhaps other processes start operating on top of them, a natural transition toward cognitive processes, which are still grounded and meaningful for the agent, has been accomplished. Therefore, unlike the original radical thesis of Brooks

(1991), an embodied approach need not be anticomputationalist or anti-representationalist (Clark, 1997). Only, our view of computation and representation may have to be broadened.

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Appendix B

Body schema in robotics: a review

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Body schema in robotics: a review

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***Abstract*—How is our body imprinted in our brain? This seemingly simple question is a subject of investigations of diverse disciplines, psychology and philosophy originally, complemented by neurosciences more recently. Despite substantial efforts, the mysteries of body representations are far from uncovered. The most widely used notions - body image and body schema - are still waiting to be clearly defined. The mechanisms that underlie body representations are co-responsible for the admiring capabilities that humans or many mammals can display: combining information from multiple sensory modalities, controlling their complex bodies, adapting to growth, failures, or using tools. These features are also desirable in robots. This paper surveys the body representations in biology from a functional or computational perspective to set ground for a review of the concept of body schema in robotics. First, we examine application-oriented research: how a robot can improve its capabilities by being able to automatically synthesize, extend, or adapt a model of its body. Second, we summarize the research area in which robots are used as tools to verify hypotheses on the mechanisms underlying biological body representations. We identify trends in these research areas and propose future research directions.**

***Index Terms*—body schema, body image, robotics, body representation, forward model, self-calibration**

I. Introduction

The basic notion of body schema encloses a group of body representations which are essential for body motion and a meaningful interaction with the environment carried out by an embodied agent. The body schema allows for integration of information from proprioception, vision, audition, the vestibular system, tactile sensing, and from the motor system in order to keep an up-to-date representation of the positions of the different body parts in space. Typically these representations are involved in movement preparation and the representation of space in different frames of reference to be used by different behaviors. Such representations are the central subject of many studies in the cognitive sciences, especially in the neurosciences. The concepts of a postural schema and a surface schema were first introduced by Head and Holmes [1]. In their view the postural schema represents the awareness we have of our bodies' position in space, and the surface schema represents our capacity to locate stimuli on the surface of the skin. Since then, many other classifications and taxonomies appeared trying to structure the plethora of body representations; yet up to now the literature has not converged to any of them.

Biological agents are able to adapt seamlessly to new situations or cope with failures. To a large extent, this is because the body representations required to support their behaviors can dynamically adapt to new circumstances. These properties are also desirable in robots; today, their operation is still restricted to static or limited environments, and resilience to failure is typically absent. When trying to bridge this gap, many roboticists look to biology for inspiration to integrate some of the features of a biological body schema into their machines. While this flow of information - from biology to robotics - was dominant so far, there also exists a route in the opposite direction. Many of the mechanisms underlying the body schema are still a mystery to cognitive scientists. Here, robots can qualify as useful tools to test hypotheses that have been put forward up to this day. In particular, although there is rapid progress, to a large extent thanks to the neurosciences with their imaging techniques, the investigation of some mechanisms requires whole brain-body-environment systems as test-beds. Experiments on robots can thus complement the research in computational neuroscience.

This paper is structured as follows. First, we offer a review of body representations in the context of biology. After discussing taxonomies of body representations and how these are supported by studies on disorders, we will focus on topics that we consider of greatest relevance for robotics: plasticity of body representations (development, adaptation, extension), coordinate transformations, and the relationship between body schema and forward models. Second, we provide an overview of the engineering-oriented work in which a body schema serves to control a robot and to improve its behavior when faced with unexpected circumstances. In theory, an enormous part of research in robotics and control could fall into this section, since models (plant models) used to control robots are ubiquitous. However, we will show how this representation is different from the ones that take inspiration from biology and further concentrate on the latter. There are many axes according to which the research in robotics could be structured. For us, the principle axis will be the nature of representation: explicit vs. implicit. Third, a section on robots employed as tools to model biological body representations is presented. We think that this body of work - investigating whole brain-body-environment systems - is a necessary complement of computational neuroscience. We conclude by identifying the major trends and suggesting future research directions.

II. Body representations in biology

Significant evidence has been accumulated up to this day testifying that there are representations of the body in the brain. It also very likely that there is no single unitary representation, but rather several, partial representations that serve different purposes. We will discuss the basic taxonomies of body representations and define the two most widely used notions: body schema and body image. Disorders and dissociation studies are useful to get insight into the structure of the putative body representations. We will discuss two in detail and present an overview of those that we consider relevant for robotics.

Body representations are plastic over time. This property is largely responsible for many of the capabilities that animals display. We will discuss the developmental time scale first. How does an infant acquire its body representation? How does it develop a sense of body ownership and agency? Then, we will review the plasticity of body representations over short time scales, minutes for instance. We will examine the "rubber hand illusion" and extension of body representations in tool use. The next topic of undisputed direct relevance for robotics are coordinate transformations. Finally, we have included a section which demonstrates the notions discussed on a concrete scenario. We also establish an explicit relation to forward internal models - a closely related concept. The idea is to provide enough information for a roboticist to get an initial functional understanding of the topic and to equip her with initial pointers to the literature. We have to admit that this section is strongly biased toward body representations in humans and primates. Other animals remained out of the scope of this review. However, studying body representations in simpler animals than humans can provide no less valuable insights for roboticists.

A. What is a body schema

Two main taxonomies form a first attempt to differentiate the variety of body representations: the dyadic and the triadic taxonomies [2]. Both draw a line between representations that are used for action and those used for perception. This functional division is grounded on the hypothesis that visual as well as somatosensory processing is carried out in two distinct nervous pathways: one for action and another for conscious perception and object recognition [3], [4], [5]. In visual processing, these are the "what" and "how" streams as suggested in [6] (earlier distinction between "what" and "where" pathways was suggested in [7]).

The visual pathway for action, the "how" or dorsal stream, goes from the occipital lobe to the motor cortex through the parietal cortex. The pathway for perception, the "what" or ventral stream, goes from the occipital lobe to the temporal lobe. A similar separation can be observed in somatosensory perception. The pathway for action involves the anterior parietal cortex (APC), eventually the secondary somatosensory area (SII) and terminates in the posterior parietal cortex (PPC) [4]; the pathway for perception involves a similar route but terminates at the insula rather than at the PPC. The right PPC might also be involved when integration of spatio-temporal information is required for the recognition of objects as well as body configuration (see also [8] and [6], [4] for a comparison between the two pathways for action and perception in the somatosensory processing and visual and auditory processing).

On these grounds, the *dyadic taxonomy* distinguishes between *body schema* and *body image*. The former are sensorimotor representations of the body used to guide movement and action, the latter are used to form our perceptual (body percept), conceptual (body concept) or emotional (body affect) judgments towards our body [3]. However, especially the concept of body image is problematic, lacking a positive definition; it seems that once we are done with a body schema, everything else can fall into body image [2]. Therefore, the *triadic taxonomy* futher splits the representations belonging to the general concept of body image [9]. One of these representations, the body structural description, entails a topological representation (mainly visual) of the position of the different body parts in relation to each other (e.g. the forearm extends the upper arm via a hinge joint). The other representation, body semantics, comprises a semantic representation of the body which includes the names of the different body parts, their functions as well as potential relations to external artifacts (e.g. shoes are used on the feet, and feet can be used to kick a football).

The functional axis, action vs. perception, is only one possible criterion to distinguish between various body representations, and an oversimplifying one for that matter. Other features used to classify body representations are availability to consciousness (unconscious vs. conscious), and dynamics (short-term vs. long-term). However, the weight of the criteria varies relative to the author and sometimes even the same notion is ascribed opposite properties (see [2] for more details). While these additional axes are useful, they still do not provide any clear taxonomy of body representations. Perhaps, such an endeavor cannot be successful, because we are not faced with two or three distinct representations, but rather with a panoply of many interacting partial representations.

Nevertheless, there is definitely some agreement that there is something like a body schema - a sensorimotor representation of the body used for action. Typically, it would not be available to consciousness[1] and would encompass both short-term (e.g. position of a limb at a given instant) and long-term dynamics (e.g. biomechanical properties and size of limbs). Since we are mainly interested in body representations in robots, this notion will be our primary focus. Our decision is motivated by the following reasons: (1) as stated above, there is certain consensus on the existence of a body schema; (2) the fact that it is a representation for action finds a natural counterpart in robots which can then be employed to perform tasks; (3) we think that robots have not yet reached the level of competence where notions like conscious representations can be investigated in a grounded fashion.

The notion of body image - as a perception-based representation - will not be excluded from our investigation; however, we will restrict it to the body structural or topological representation, leaving apart the domains of body concept or body affect.

B. Disorders

What are the grounds on which the body representations are classified into the taxonomies we have come across? Underpinning these taxonomies are a variety of studies which analyze the functional impact of some impairment on the behavior of a subject (see [4]). It is the fact that some subjects

[1]Though it may become conscious under certain circumstances, such as during motor imagery [9].

are able to perform normally on some body-related tasks but not on others that allows to distinguish between the different representations.

Probably the most mentioned disorder in the context of research on body schema is that of deafferentation. Deafferentation in general is the (total or partial) deterioration of afferent signals, i.e. signals that go from the periphery to the central nervous system. When applied to body-related representations, deafferentation is the (complete or partial) loss of proprioceptive and tactile signals whether their origin is in the periphery or in more central areas. Paillard [5] reported two cases of deafferented patients with very different behaviors. In one case, the patient G.L. was able to perceive a signal applied to her body, report verbally the location of the stimulus as well as to point to the correct location of the limb part stimulated on a body sketch. However, when asked to point with her right hand to the part of her own body which had been stimulated, she was unable to do so. In the other (somehow more bizarre) case, patient R.S. was unable to consciously perceive tactile stimuli, joint positioning, temperature or pain in her own body; she could for example cut or burn herself without noticing. R.S. failed to locate verbally a given tactile stimuli on her own body but curiously (even to herself) she could point flawlessly to the body part stimulated. According to Paillard, these two cases provide a case for an intact body schema with an impaired body image (R.S.) and a case for an impaired body schema with an intact body image (G.L.); i.e. they provide a case for the distinction between the two body representations in the brain as mentioned in the previous section [3].

Cases showing a further distinction between body structural description and body semantics can also be found in the literature. In a large group study, Schwoebel and Coslett [9] analyzed subjects on three types of measures: one accessing the integrity of the body schema, one accessing the integrity of the body structural description, and another accessing the integrity of the body semantic representation. Each performance measure involved a set of different tasks [9]. In the first measure, aimed at accessing the integrity of the body schema, subjects were required either to (1) imagine or execute different finger movements, or (2) to indicate the laterality of a hand in a picture (i.e. left or right hand). The second measure, aimed at accessing the body structural description, included three tasks: (1) to point to the location in one's own body of a body part depicted in an image, (2) to point to the location of a stimulus applied to a given body part, and (3) to point to one of three pictured body parts that were closer to a given target body surface. The third measure, aimed to access the integrity of the body semantic description, involved two tasks: (1) to match one of three pictured body parts with another functionally-related target part (e.g. the elbow has as similar function as the knee; they are both hinge joints), and (2) to match a pictured item of cloth with one of four given pictured body parts. They found out that 13 of the patients analyzed failed on tasks involving the measure of body schema integrity but performed normally on the other two measures. Three of the patients failed to carry out successfully the tasks involved in the body structural description measure, but were able to carry out normally the tasks involved in the other two measures. Finally, two of the patients failed to execute the tasks related to the body semantic measures but performed normally in the other tasks. These results provide grounds to support the triadic taxonomy.

TABLE I
DISORDERS RELATED TO THE BODY SCHEMA (EXTRACTED FROM [2]).

Alice in Wonderland Syndrome	Distorted awareness of body size, mass, or its position in space
Allochiria	Mislocation of sensory stimuli to opposite half of the body
Anarchic hand sign	Unintended but purposeful movements of the upper limb and intermanual conflict
Autoscopy	Experience of seeing one's body in extrapersonal space
Autoprosopagnosia	Inability to recognize one's own face
Autotopagnosia	Mislocalisation of body parts and bodily sensations
Body form agnosia	Deficit of recognition of body parts
Body-specific aphasia	Loss of lexical knowledge of body parts
Deafferentation	Loss of tactile and proprioceptive information
Dysmorphophosia	Distorted perception of one's self-appearance
Fading limb	Lack of awareness of the presence and position of the limb if not seen
Finger agnosia	Inability to individuate and recognize the fingers
Gertmann's syndrome	Finger agnosia, agraphia, acalculia and left-right confusion
Heterotopagnosia	Designation of parts of the body of another person when asked to point towards one's own body
Ideomotor apraxia	Inability to execute or carry out skilled movements and gestures
Macro/microsomatognosia	Distorted awareness of body or body parts' size
Mirror sign	Inability to recognize one's own image in the mirror
Motion sickness (or kinetosis)	Vestibular balance disorder
Motor neglect	Underutilisation of one side of the body
Numbsense	Tactile deficit with preserved tactually guided movements
Out of body experience (OBE)	Visual awareness of one's own body from a location outside the physical body
Personal neglect	Lack of attention towards one's side of the body
Phantom limb	Awareness of an amputated limb
Pusher syndrome	Postural deviation towards the contralesional side
Prosopagnosia	Deficit of face recognition
Supernumerary limb	Awareness of non-existing limbs
Tactile extinction	Lack of awareness of tactile stimuli on the contralesional limb during simultaneous bilateral stimulation

If robots are to be used as models of biological (in this case human) body representations, they can eventually be also subject to such tests - failures in robots can be compared to disorders in humans. A list with main disorders related to body representations is given in Table I. This list is a short version of the one offered in Vignemont [2]. The original table was pruned in order to give only the information most relevant for roboticists; the disorders removed were basically related to eating disorders or emotional responses related to body representations.

C. Plasticity of body representations

1) Development, body ownership, agency: How do the various body representations originate? They arise during the process of development immediately after birth (or even before - in the womb). We have to rely more on psychological rather than neurophysiological data here, since brain imaging techniques are not readily applicable on infants. As reported by Rochat [10], infants spend substantial time in their early months observing and touching themselves. Rochat calls it the visual-proprioceptive calibration of the body. Through this process of babbling, intermodal redundancies, temporal contingencies and spatial congruences are picked up. Environmental stimulation (single touch) can be distinguished from self-stimulation (double-touch + proprioceptive stimulation) [11]. If we treat this process as relying mainly on perception, we can view it as the acquisition of the body image. However, the infants not only observe, but actively involve their motor apparatus in the explorations (e.g., [12]). Hence, the development of body schema probably takes place at the same time.

Hand in hand with the development of the body representations, the infants acquire a notion of *body ownership* and *agency*. By sense of body ownership we mean that the infant knows that it is its body that is moving, even passively; sense of agency corresponds to the notion that the infant (or agent) knows that it is causing or generating an action. We mean agency in a low-level sense here - pre-reflective, sensorimotor, and functional, rather than in a phenomenological sense (see e.g. [13] for a disambiguation). Basically, a sense of body ownership would be disrupted by a sensory experience that does not match the previously learned regularities between modalities (i.e. mismatch with body image); sense of agency would be disrupted by a sensory-motor mismatch (i.e. a mismatch with a body schema).[2] However, as it is hard to separate body image from body schema, it is also hard to separate sense of body ownership from sense of agency (see [14] for details and experimental treatment of this issue). The above-mentioned low-level capabilities constitute the basis for action recognition in self, action recognition in others, and self-other discrimination. This is further related to action mirroring (where the mirror neurons are active) and imitation (see Rizzolatti *et al.* [15]). Such capabilities constitute a natural extension of our topic, but will remain largely out of the scope of this review.

2) Rubber hand illusion: The body representations are not only plastic during development. They can also respond to large changes in the body, such as limb loss (see e.g., Ramachandran and Blakeslee [16]). Moreover, body representations can also adapt over much shorter time scales. Let us first look how this can happen on the perceptual side - modifying the body image. Holmes and Spence [17] made an extensive review on different behavioral, neurophysiological and neuropsychological studies regarding evidence on the possibility to "incorporate" objects not connected directly to the body by multisensory integration. A prominent series of studies, started by Botvinick and Cohen [18], involves the "rubber hand illusion". A subject looks at a rubber replica of her hand while her own hand is hidden. Through simultaneous tactile stimulation of the subject's hand and the rubber hand, visible on the rubber hand only, the rubber hand becomes incorporated into the body image and the subject is deceived to think she "owns" the rubber hand. In other words, simultaneous tactile stimulation, together with congruent visual and proprioceptive feedback, causes a rapid adaptation of the body image and the rubber hand enters our sense of body ownership. Graziano [19] reported a similar phenomenon in monkeys as well. More recently, other studies ([20], [21], [22], [23]) further explored the rubber hand paradigm, also in the case of hand amputees [24]. The appropriation of the external object as part of the body representation of the person goes to the extent that if the rubber hand is threatened, the person shows a similar level of activity in the brain areas associated with anxiety and interoceptive awareness [25]. This effect can be found in the appropriation of virtual bodies as well [26].

3) Tool use: Tsakiris *et al.* [14] pointed out that the basic rubber hand illusion setup lacks ecological validity, because it does not involve bodily movement. In other words, it is not a usual situation for primates or humans not to actively perform actions, but rely on multi-sensory integration only. Efferent information may play a key role, bringing us back to the difficulty of separation between body schema and image, or body ownership and agency. This leads us to another prominent experimental paradigm: *body schema extension* during *tool use* (body schema because now we are concerned with representations for action). Primates can manipulate objects in different ways and some can use tools to achieve a particular goal. Maravita and Iriki [27] investigated the integration of a tool into one's body schema in a macaque monkey that was retrieving food with the help of a rake. Neuronal activity of bimodal neurons (i.e. neurons that react to both somatosensory and visual stimulation) was recorded from the intraparietal cortex. Two groups of neurons were identified: "distal type" and "proximal type" (see Fig. 1). The former responded to somatosensory stimuli at the hand and visual stimuli near the hand. The visual receptive field (region of space in which the presence of a stimulus will alter the firing of a particular neuron) of these neurons followed the hand in space. After the monkey had used the tool for about five minutes, the visual receptive field of some neurons expanded to cover the entire length of the tool (Fig. 1 (c)). The visual receptive field of the latter neuron group - the "proximal type" - was not centered around the hand, but spanned the whole space within reach (Fig. 1 (g)). This space is called *peripersonal space*. As the body and the space immediately surrounding it are always in close interaction, the same seems to hold for their representations. Therefore, the representation of the body and of peripersonal space - space within reach - have to go hand in hand [28]. In the monkey, this space was expanded accordingly after working with the tool to accommodate the whole space that can be accessed with the tool.

Several studies ([29], [30], [31], [32], [33], [34]) followed that show the ability of the primate brain to incorporate tools into its body representations and use them for coordinated action. The visual receptive field was extended by the tool when it was used for retrieving food, but not when the monkey just held the rake passively in its hand (Fig. 1 (d)). This confirms the hypothesis that action context plays a key role. It is also probable - unlike in the rubber hand illusion scenario - that the subject is not fully "deceived" to think that the tool

[2]In more concrete terms, this means there will be a mismatch between the sensory feedback predicted by a forward model from a motor command (efference) copy and the actual sensory input (reafference). This is also referred to as the "comparator model". However, for both body ownership and agency, the situation is more complicated and involves a top-down component as well - knowledge about the context [13], [14].

is part of her body - the tool does not look like the hand - but only incorporates it into the representation in order to be able to use it as a "body auxiliary" [14].

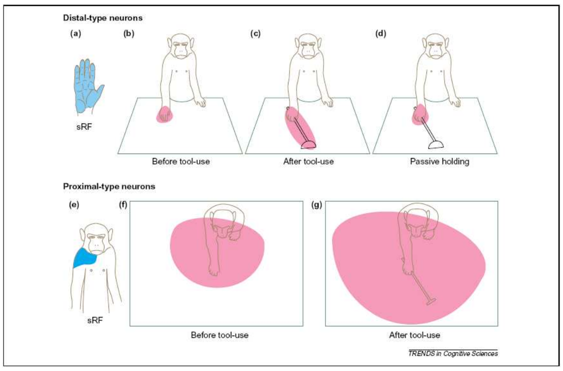


Fig. 1. Changes in bimodal receptive field properties following tool-use. The somatosensory receptive fields (sRF) of cells in this region were identified by light touches, passive manipulation of joints or active hand-use. The visual RF (vRF) was defined as the area in which cellular responses were evoked by visual probes (the most effective ones being those moving towards the sRF). (a) sRF (blue area) of the "distal type" bimodal neurons and their vRF (pink areas) (b) before tool-use, (c) immediately after tooluse, and (d) when just passively grabbing the rake. (e) sRF (blue area) of "proximal type" bimodal neurons, and their vRF (pink areas) (f) before and (g) immediately after tool-use. Reprinted from [31] with permission.

4) Intelligent tools: A tool can be much more than a passive rake. It can be an artifact with "intelligence" of its own. Slater *et al.* [35] show how it is possible to induce the incorporation of virtual bodies in the body representation. The advances in Brain-Computer interfaces ([36], [37], [38]) have made it possible to use biological signals to control robotic devices, enabling their users to perform activities otherwise out of their reach. These interfaces allow direct interaction with cortical processes that the user can control. So far evidence with monkeys ([39], [40]) show that they can "incorporate" intelligent devices into their body representation. Other studies with amputees ([41], [42], [43]) present evidence of changes in the cortical activation due to the interaction with an intelligent prosthetic hand.

Taking the "intelligence" of the artifact or device one step further, Sanchez *et al.* [44] and DiGiovanna [45] explore symbiotic systems where not only is the artifact incorporated in the body representation of its user, this time a rat, but at the same time, the intelligent artifact actively participates in the process. The artificial system taps into the user's brain and uses reinforcement learning to modify its own parameters in order to maximize the match between the user's intention and the action performed with the artifact. Thus, both the user and the tool co-adapt to accomplish the task.

It is not hard to imagine how the plasticity of body representations, which was discussed in this section, can be useful for robots. A robot that can automatically acquire a model of itself that can then be used for control will save a lot of work to programmers. If it is able to automatically adapt the model to new circumstances - body extensions, wear and tear, or even substantial failures - it will lead to a new generation of robots which can leave their restricted work conditions.

D. Coordinate transformations

A key issue that is often mentioned in the context of the body schema is the one of coordinate transformations. The problem is simple to formulate but hard to tackle. Imagine you see an orange at some location in space and you want to grasp it. It might seem trivial for you to simply stretch your arm and reach it, but how is the brain successful at it? The orange falls on some location in the retina, which is dependent on the position of the eyes, the head, and the torso; if you move either of them (or all, as far as their movements do not cancel out) then the location of the orange in the retina will change accordingly. To perform a particular movement the brain has to have (in principle) at least one stable frame of reference (FoR), i.e. a FoR which is invariant to changes in the position of some of your limb parts (say, the eyes or the head). A stable FoR for reaching is the torso frame of reference, since all the movements of the hand have to be necessarily executed in relation to the torso - due to the physical structure which connects the two limb parts. However, to have the position of the orange encoded in relation to the torso, the brain has to convert first the retina coordinates into eye coordinates using the location of the orange in retina, then transform the position in eye FoR to the head FoR using the current orientation of the eyes with respect to the head, and finally transform the location of the object with respect to the head into torso FoR using the orientation of the head in relation to the torso.

The brain areas which are often mentioned in the context of body schema and coordinate transformations are: the lateral intraparietal area (LIP), which encodes information relevant for saccadic eye movements [46], the ventral intraparietal area (VIP) which encodes both visual and somatosensory information [47], [48] and is connected to LIP area [49] and premotor areas responsible for head movements [50], the parietal reach region (PRR) which encodes reaching information [51], and the anterior parietal area which encodes grasping information. Each of these areas seems to use different frames of reference. This would be expected as different behaviors might benefit from a different encoding. For example, parts of LIP and VIP are supposed to represent the position of a visual target in both eye-centered and head-centered coordinate systems [52], [47]; neurons in the PRR should have the eye as their reference frame [51]. Interestingly, other neurons in the PRR have also been found which seem to encode the difference between a target in eye FoR and the current position of the hand also in eye FoR [53]. Such neurons seem to be particularly suited to output an error signal with the distance between the hand and the target [53]. Similar neurons have also been found in area 5 of the posterior parietal cortex, which is adjacent to the PRR (see [54]).

But how does the brain compute these coordinate transformations? In the classical view (coming from geometry and applied in robotics, for instance), coordinate transformations are computed explicitly and applied sequentially; for example to pass from eye FoR to hand FoR, the brain would compute all the required transformations in series between the eyes and the head, then between the head and the torso, and finally between the torso and the hand. We will see examples of this approach throughout the robotic part of the paper, in particular in Section III-C. However, in a novel view, coordinate transformations can be computed implicitly and in parallel [55]. The above mentioned neurons which encode for the difference between the hand and the target are a good example of such a view. In this particular case the only modality used for the coordinate transformation is vision; the positions of the hand and the target are both acquired from the visual input. In fact, relatively little is known about the influence of proprioception for computing coordinate transformations.

One of the most relevant findings in brain research on coordinate transformations is that of gain modulation (also called gain fields, or fields of gain). Gain modulation consists of "a change in the response amplitude of a neuron that is not accompanied by a modification of response selectivity" [56]. It is a nonlinear way of combining information from two or more sources, let them be sensor, motor, or cognitive. Typically gain fields are used within a population based encoding, in which several neurons respond to a region of space. The use of a population based encoding combined with gain fields for coordinate transformations is depicted in Figure 2. The plots show the reconstruction of the signal obtained from a population of five neurons (circles below the plots). As can be seen when the stimulus (the star) is on the left side of the fixation point (filled circle), the neurons in the left part of the plot are more active than the ones on the right part (A and C); when the stimulus is located on the right side of the fixation point the neurons on the right part of the plot are more active than those on the left part (B). The plots on top show the response selectivity of each particular neuron in retina frame of reference; in A and C the response of the neurons to the respective stimulus is very similar as the stimulus falls on the same location of the retina. However, in the neurons that encode the stimulus in head-centered frame of reference, the amplitude of the neural responses changes with respect to (i.e. is modulated by) the current position of the eyes. While in A the eye position increases the amplitude response of the active neurons, in C it does not. This result can be achieved by multiplying the responses of eye position signal with the position of the stimulus in retina frame of reference [57]. For instance, the parts of LIP and VIP discussed above (with position of a visual target in both eye-centered and head-centered coordinates) have gain fields that depend on gaze direction, leading to body-centered coordinates useful for gaze control and object reaching [58], [47].

E. Body schema and forward models

While the taxonomies (Section II-A) help us to roughly define the landscape of body representations, they still stop short off a concrete enough characterization that would allow one to build a computational or robotic model. The goal of this section is to illustrate some of the concepts put forth in the previous section on a simplified, but concrete enough, scenario and to clarify the relationship of body schema to the closely related concepts of peripersonal space and forward models.

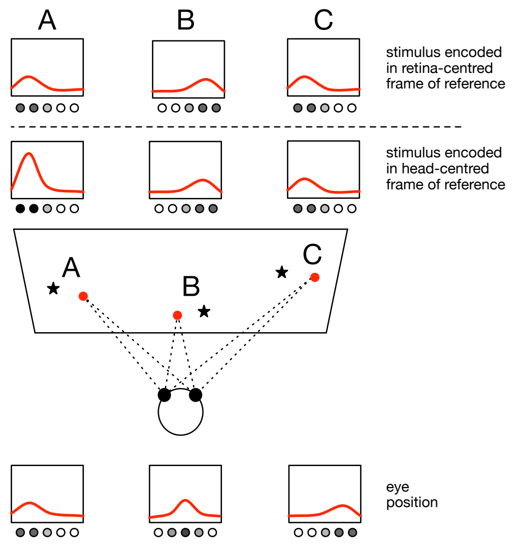


Fig. 2. Population based encoding combined with gain fields to achieve coordinate transformations between a retina-centred FoR and a head-centred FoR (see text for details).

Figure 3 presents a didactic biologically motivated scenario, where an agent is interacting with an object on a table. The top part of the figure shows the agent and its visual field on the right, and a corresponding hypothetical neural architecture on the left. We have included three modalities: visual, proprioceptive, and tactile. In the visual modality, there are two hypothetical neural ensembles: one corresponding to the image on the camera (retina), and another which represents the same image in a body-centered reference frame. The position of the object as well as the hand is displayed in the activation. The transformation to the body-centered view is achieved by combining the camera image with the position of the head. Whereas regarding the position of the object, there is only visual information available, the location of the hand can also be obtained from proprioception in arm and hand.

Where is the body schema in this schematics? We offer the following interpretation: the activations in the individual neural fields are the *short-term body schema* - they represent the position or configuration of the body at one particular instant. The links between the neuronal ensembles, on the other hand, belong to a *long-term body schema*[3]. They are relationships between modalities that hold, at least over the here-and-now time-scale, and that can be used to perform coordinate transformations and to combine redundant information, such as regarding position of one's hand, in an optimal fashion.

Until now, only sensory modalities were involved. However, to move from one configuration to another, a motor action is required. A particular activation of arm and hand muscles can bring the agent to the situation at the bottom right part of

[3]For reasons of simplicity, there are direct cross-modal mappings in our scenario. However, multimodal neural ensembles, i.e. those that fuse multiple modalities, were also reported in the brain. Similar connectivity could nevertheless apply to them as well.

Figure 3, where it has moved the object in front of its single eye. Can the agent also learn about the mapping from the initial to the current state? The motor modality has to enter our representation, bringing us to the concepts of forward and inverse models (e.g. [59], [60]). These concepts come originally from control theory but were adopted by the field of human motor control. Given the current sensory state and the motor command (or its copy - efference copy), a *forward model* can predict the next sensory state (or predicted sensory feedback - corollary discharge, bottom-left in Figure 3). The so-called *inverse model* is a mapping in the opposite direction. Given a target (goal) state, and the current state, this model provides the motor command needed to reach the goal state. *Peripersonal space* can finally be also identified in our schematics. It is the space within reach; therefore, one possible instantiation would be part of the visual space, for which we can find a motor command (using the inverse model) to reach that space.

Forward models bring several advantages. For instance, the predicted sensory signals can be delivered before the real ones and can be exploited for control, or they can be compared with the real reafference and integrated to give a more reliable state estimation, or used to separate the expected effect of the agent's actions from unexpected intervention from the environment. As Grush [61] points out, the forward or inverse model (Grush uses the term emulator) can be either a look-up table storing previous input-output sequences, or it can be an *articulated model* - a model that includes some variables corresponding to their counterparts in the musculoskeletal system (e.g. elbow angle, arm angular inertia, tension on quadriceps). Some of these variables can be measured (e.g. by stretch receptors) and these sensors can also be simulated in the emulator. Marques and Holland [62] propose to call the model that produces imagined sensory states more or less directly *unmediated*, and a model that produces them using a more or less complex self-simulation interacting with a simulated world *mediated*.

It should be clear by now that a body schema involves relationships between sensory modalities (such as coordinate transformations or integration of redundant information from modalities) and relationships between sensory and motor modalities. In our didactic scenario, these two components were separated - cross-modal mappings were between sensory modalities, whereas a separate forward model was dealing with a mapping between two sensory states, given a motor action. Such a division is very tempting and convenient for a robotic implementation. However, the biological reality may be more complex and it may not be possible to dissect the sensorimotor loop like this (see e.g. O'Regan and Noe [63] for a detailed account). Finally, the body schema has to involve not only spatial, but also biomechanical information, and it has to be plastic over time.

III. Improving robot behavior through a body schema

Like natural agents, artificial agents can also acquire sensorimotor representations of their own bodies and use them to guide actions. However, before we discuss the character that such a model can have, we will discuss whether models or representations are in fact needed altogether. After, we will classify the various forms that a body schema of a robot can take. We have used the nature of representation (explicit vs. implicit) as a primary axis to divide the spectrum of body representations. Regardless of the representation, the key issue will be automatic acquisition and adaptation of a body schema. In particular, the application scenarios will include: recognition of own body, acquisition of its model, and its extension or adaptation when using a tool or after failure.

A. Does a robot need a model?

The necessity for models of the world as well as of the robot itself comes as natural both to followers of Traditional Artificial Intelligence or GOFAI (Good Old-Fashioned Artificial Intelligence") [64] as well as to control engineers. The former work with symbolic models of the robot and the world, the latter use typically analytical models of the controlled system - plant models. This stance - that models, or representations, are necessary to produce useful behaviors - was challenged by the so-called new AI, behavior-based AI, or embodied cognitive science [65], [66]. New AI demonstrated the potential of robots that do not rely on representations, but rather on embodiment, and that exploit the interaction with the environment [67]. Relating back to our topic and paraphrasing Brooks, to what extent can it hold that "the body is its own best model"?

1) Intelligence without representation: It has been shown by the proponents of behavior-based AI that many remarkable behaviors can be achieved without a model. Examples are the achievements of Grey Walter [68], and Valentino Braitenberg [69] with purely reactive agents - agents that have no internal states, but only direct connections between sensors and motors. Another case in point that illustrates that a lot can be achieved without representation is the subsumption architecture of Rodney Brooks [70], [71]. Inspired by biological evolution, Brooks created a decentralized control architecture consisting of different layers. Every layer is a more or less simple coupling of sensors to motors (responsible for obstacle avoidance, for instance). Though in this architecture the individual modules may have internal states (as they are Finite State Machines), Brooks argues against even implicit representation here [65]. The 'insect' robot Ghenghis [71] or the control architectures used by Cruse [72] demonstrate how a reflex-like controller can give rise to a walking pattern. There is no plan or model for the behavior in the robots' control architectures - walking arises only through the interaction of the body with the environment and simple sensor-actuator connections.

2) Model – benefits and costs: Before we ask ourselves the question, what is the best body representation for a particular robot, following up on the the previous section, we propose to ask another question first: what are the benefits and costs of having a model of the robot's body?

The benefit number one typically is that the model of a robot (or plant) can be used for control. For instance, while multi-DOF robotic manipulators can be precisely controlled

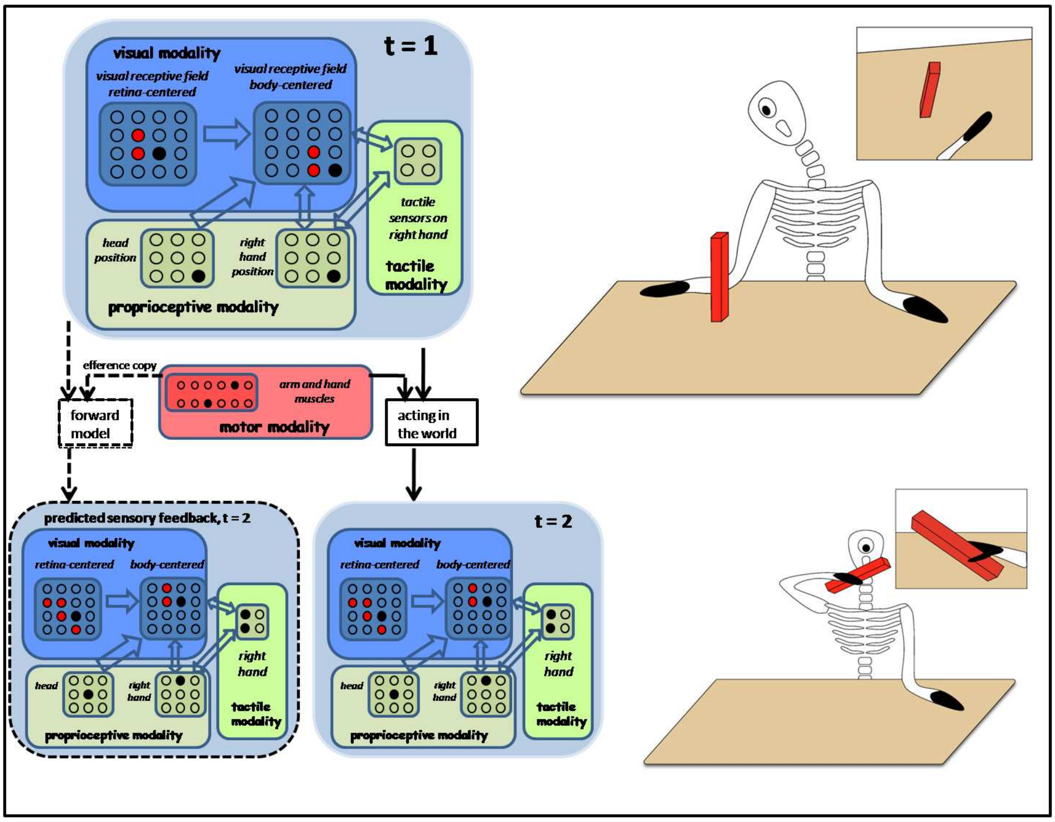


Fig. 3. Long-term and short-term body schema, and forward models. This figure presents a simple biologically-inspired scenario to illustrate the concepts. An agent is depicted on the right at two different time steps, while trying to grasp an object. The small window in the top-right of each picture shows the view from the agents single eye (or camera). The left part depicts hypothetical neuronal ensembles of different modalities, their connections, and activations. Let us look at the initial situation (top). The agent is looking to the right and sees a red object in the center of its visual field (red activation in the retina-centered neurons) and its hand slightly right from it (black activation). However, with respect to the agent's body, the object is to the right and down. The retina-centered visual neurons can be combined with proprioception from the head muscles (black activation in the head position neurons) to perform a frame of reference (or coordinate) transformation, resulting in the activations in the body-centered visual neurons. Regarding the position of the hand, there is additional information from proprioception in the hand. The coordinate transformation between the visual modality (where the hand is seen) and the proprioceptive can also be performed and the two sources of information can be combined (double arrow between them). The bottom right part of the figure depicts a situation where the agent has grasped the object and moved it in front of its eye. The corresponding activations in the modalities are updated (object on the retina is much bigger, head and arm have moved) and there is a new activation in the tactile modality - on the agent's palm. The bottom left part illustrates the concept of a forward model: based on the multi-modal map at t=1 and a copy of a motor command, a prediction of the sensory map at t=2 arises.

using the models and associated control techniques that were developed [73], to our knowledge, it is not feasible to control such a plant without a representation of any sort. With a precise representation of the robot's body - its kinematics and dynamics, including the actuation mechanism - it can be used for precise feedforward control with little or no feedback. In controlled environments, such as industrial settings, this is sufficient. If feedback is present, the mappings from motors to sensors can also be learned, giving rise to a forward model (see Section II-E). Such a model can also be used to improve closed-loop control: sensory feedback can be predicted in advance - before it is actually received - and control action can be adapted (see e.g. [74]). This is especially useful when the feedback comes with a significant delay. The fact that the expected feedback can be predicted can be also used to distinguish self-generated sensory information from sensory input generated by the environment. An account of similar scenarios in insects is provided by Webb [75]. A more elaborate and decoupled forward model, i.e. a model that can be iterated without actually executing the motor actions in the real world, can be used for planning of whole action sequences. Based on the predicted consequences, an appropriate action can be selected (e.g., [62]). As the last benefit, if the model includes a temporal dimension and uncertainty, using probabilistic terminology, it can be used to perform not only prediction, but also filtering (computing the belief state - posterior distribution over the current state)

However, we should not forget that there are costs associated with having models or representations. Such a model needs to be developed and that has costs attached to it. Heikkonen and Koikkalainen [76] report that robot programming - a substantial part of which is the development of the robot's model - accounts for about one third of the cost of an industrial robot system. The model is developed by engineers and given to the robot. This may be acceptable if the job has to be done only once - before the robot is put in operation. However, problems arise if the conditions change over time; this can be due to deformations of body parts from wear and tear, but it can also be due to more dramatic changes such as change of topology of the robot or the robot using a tool. In such situations, a significant part of the model would have to be reprogrammed giving rise to additional costs - model maintenance costs. This motivates the research in automatic model acquisition and adaptation.

B. What is body schema in a robot?

It seems that in order for a robot to be able to perform a goal-directed action, two components are essential. First, to perform the action itself, it is often necessary to know at least some of the parameters of the system to be controlled. Second, if the robot relies on its own sensory system and if the goal is expressed in one of the sensory modalities (such as an object to be grasped in sight of a camera), a mapping between the sensory and motor modalities has to exist [77]. These two components can be almost completely separated or they can be completely intertwined. In robotics and control theory, the separation is typically clear. Even in the biological realm, there are indications that sensorimotor representations operate on kinematic variables, while the details that are necessary to perform a particular movement (an inverse dynamics model of the 'plant' which needs to include inertia, stiffness, possibly actuator dynamics etc.) can be delegated to other control structures (such as cerebellum and the spinal cord [78]) and to the body itself.

Let us first look at a prominent scenario, a multi-DOF robotic manipulator. The typical goal is to make the end-effector reach a certain point in the workspace. While the goal is typically expressed in Cartesian or visual space, motor commands will be issued in joint space. Thus, a coordinate transformation between the two spaces is essential (confront with Section II-D and with the notion of peripersonal space in Section II-C3). An example of such a mapping is inverse kinematics, i.e. the manipulator joint angles needed to achieve the desired position and orientation of the end-effector in Cartesian space can be obtained. In industrial settings, a manipulator can often operate based solely on the kinematic model, without visual feedback. The dynamics (forces/torques needed to achieve desired positions) can be delegated to another subsystem (e.g. feedback controllers within servo motors), or a separate dynamical model of the plant can complement the kinematic model. We call model used in this case *explicit*. The kinematics (and dynamics) are described by equations; the parameters, such as segment lengths and orientation of joints, are measured and inserted into the equations. The platform and its model are then carefully calibrated. We can call the model also *objective*; an attempt is made to objectively measure the physical reality of the robot and input it in the model. Yet, we are dealing with a representation of the robot's body that can be used to guide actions, and thus it can be classified as a body schema. For us, however, it will lie on one end of the spectrum of research and we will discuss it only briefly. First, because we feel that such a model departs too far from the properties that we attribute to a body schema; contrary to its biological counterpart, this model is typically fixed, explicit, precise, and centralized. Perhaps even more importantly, it involves minimal or no perception; it is given from the outside and thus relies on information that biological agents cannot access. Second, modeling and control of robotic manipulators (e.g., [79], [73], [80]), or robots in general (e.g., [81]), is already an enormous research field in itself.

Articulated models come closer to the notion of body schema as we know it from biology. Recall from Section II-E that an *articulated model* is based on state variables (such as manipulator joint angle positions) that interact according to the laws of dynamics and mechanics [61]. This time, however, the variables have to be measured by the robot's own sensors. Hersch *et al.* [82] hence use the term *subjective body schema*. Usually, the definition of state variables comes from the outside with prior knowledge of the problem. The model can still have a form of equations, as in [82]. However, we will regard even a body schema that does not have a mathematical form as explicit, if there is a one-to-one correspondence between the body parts of the real robot and those in the model, as in [83]. Articulated models will be discussed together with explicit models.

Explicit models have a number of advantages. The sensorimotor mappings as well as plant models are governed by explicit equations, and hence it is possible to calculate the behavior of the system even in previously unseen situations. Also, as they are more transparent, it may be easier to debug them and to assess their performance. However, as the plant and sensorimotor mappings become nonlinear (imagine a compliant pneumatically driven robot with multiple modalities), a closed-form solution may not exist. Platforms that cannot be modeled explicitly will be addressed by *implicit models*. Such a body representation can be a simple look-up table with previously encountered sensorimotor relationships, or, neural networks often serve as the substrate for an implicit body schema. These models are typically more bio-inspired and will close the section on improving robot behavior through a body schema. At the same time, they will provide a natural transition to Section IV - that deals with robots as tools to model biological body representations.

The representations of the robot's body, as discussed above, contain the long-term properties of the plant and hence correspond to the notion of a long-term body schema (cf. sections II-A and II-E). However, what is no less important is a short-term representation of the body - where it is in space right now, for instance. Current sensory readings have to be mapped onto some states (if there are states) in the long-term body schema and can then be used to plan future actions, for instance. The short-term body reprepresentations can have a "winner-take-all" form, or they can have a probabilistic form, where alternative states are possible, with given probabilities (cf. gain fields and population based encoding in Section II-D).

The most prominent studies - using both explicit and implicit representations - that we will review are summarized in Table II.

C. Explicit models

Fixed kinematic models will start off the section concerned with explicit representations of robot bodies. Then we will move to adaptive models - models that can self-calibrate or that can even learn the topology of the body structure. These models are inferred using the robot's own sensors and hence are subjective, even though the perception is typically simplified. Finally, we will discuss models of the robot's body that also include dynamics.

1) Fixed kinematic models: Let us briefly look at a multi-DOF robotic manipulator again. It operates based on its forward and inverse kinematic functions that ensure the coordinate transformation between the workspace (a Cartesian coordinate system in which the goal for the end-effector is expressed), and the joint space. The joint positions can be directly used as target commands for servomotors[4]. If the manipulator is accompanied with a fixed camera that is observing the environment, an additional frame of reference transformation from the camera frame reference to the Cartesian or task space has to be defined.

What are the limitations of this architecture? First, a fixed kinematic model applies to robots obeying rigid body dynamics only. Second, the model is designed from the outside and is not adaptive. New calibrations have to be done in response to plant drift (e.g. robot's wear and tear). A change in the robot's geometry or the addition of a tool might require a new model. Third, this approach is not easily extensible to include more modalities (such as touch). Additional nonlinear sensorimotor mappings and their integration cannot be dealt with by the current analytical machinery. Fourth, since dynamics was not addressed by the kinematic model, this solution has variable performance in different tasks, where the end-effector has to apply force, or when external forces such as gravity loading change, or with plants that cannot be directly position controlled (e.g. pneumatic actuators). All these shortcomings will be addressed in the following sections.

2) Self-calibration of a parametrized kinematic model: Self-calibration of a parametrized kinematic chain can deal with changes in geometry over time (such as changes due to material fatigue). Automatic calibration is only possible when the system receives information from more than one source. For instance, the calibration of a camera-manipulator system can be achieved automatically by comparing the position of an end-effector as observed by the camera with the one from the forward kinematic function (after they have been converted to a common, typically Cartesian, reference system). Leaving the human engineer out of the loop can reduce costs. As a special case of self-calibration, we include body schema extension in this subsection. Automatic calibration of a model is addressed by some traditional methods from machine learning [84], system identification [85],[86], or probability theory [87]. More specifically, there is a number of solutions to the automated calibration of a kinematic chain [88], [89], [90] or a hand/eye setup [91]. Typically, a sampling period in which different configurations are visited is followed by an optimization procedure.[5] However, rather than "batch adaptation", it is desirable to develop systems that learn incrementally and online, following the inspiration from biology.

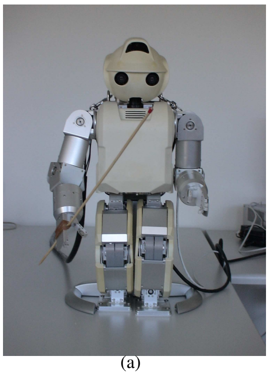
Hersch *et al.* [82] present an extension of the self-calibration approach. Taking advantage of prior knowledge of its kinematic structure (number, arrangement and type of DOFs), a simulated 24 DOF humanoid robot is able to learn the missing parameters of the kinematic chain - position and orientations of joints - by observing its body with a camera. A gradient descent algorithm is then applied, the efficiency of which increases when additional joints, not only the end-effector, can be observed. On a real robot (Hoap3, see Fig. 4), it was demonstrated that the algorithm can cope with the incorporation of a stick as an extension to the body within 2 or 3 minutes (cf. Section II-C3). In [93] this system is complemented by learning the neck-eyes kinematic chain using optical flow, and the whole system is demonstrated on the iCub humanoid robot. There are a couple of features that bring this work closer to the biological notion of body representations. First, contrary to the standard calibration approaches in which a phase of sampling and optimization precedes the actual use, the algorithm of Hersch *et al.* [82] works online. Second, it is a case of a 'subjective body schema'. The system is self-contained, or situated, in the sense that the sensorimotor mappings learned are solely based on the information acquired from the robot's own sensory and motor signals. The geometrical properties of the robot, such as the segment lengths, of course mediate the sensorimotor relationships, but cannot be accessed directly. The correspondence between the different reference frames, e.g. from end-effector to head with the camera, is given by the kinematic chain parameters which are subject to learning. Thus, there is no pre-coded transformation given from the outside, such as one from a camera to Cartesian frame.

Martinez-Cantin *et al.* [94] presented an improvement in efficiency over the work of Hersch *et al.*. First, they employed a more efficient learning method than gradient descent for estimating the body schema parameters: a Recursive Least Squares (RLS) estimator. Second, they explored the configuration space in an intelligent way, looking for the most informative measurements based on the posterior uncertainty from the RLS.

Nabeshima *et al.* [95] also employ a traditional kinematic controller. However, the problem they address is not self-calibration, but specifically body schema extension and the detection of such a change. An upper humanoid torso is used to reach for objects. Apart from proprioception (joint angles) and vision, a third modality, touch, is involved. When the robot hand touches a target, a learning process - spatiotemporal integration of the multimodal information that preceded the contact - is triggered. This can be retrieved later from an associative memory and used to drive a controller. When the robot arm is extended with a stick (a primitive tool), contacts occur in new situations, and a new kinematic controller is learned in response. Neural networks are employed to imple-

[4]This is often the case in robotics: proprioception from joints can at the same time act as a motor command - it is the target position sent to a servomotor. However, although this simplification may be convenient, we have to be aware that it departs from biological reality.

[5]This is not the case for the exploration-estimation algorithm [92] though, where the exploration strategy is more sophisticated and intertwined with the model evaluation stage.



(a)

(b)

Fig. 4. Robot and its body schemata. (a) Hoap3 robot. (b) Body schema. Left:"real" schema. Middle: body schema learned by looking at hands and feet only. Right: body schema learned when looking at additional joints. Hersch *et al.* [82]

ment the spatiotemporal integration and learning. This work is much more bio-inspired than what we have encountered and will encounter in this section. However, as no explicit correspondence with biology is established, we do not classify the work as biological modeling (an example of which, Hikita *et al.* [96], will be presented in Section IV).

3) Automatic model synthesis including topology: In this section we review robot kinematic models that can be synthesized automatically with little prior knowledge. Contrary to the previous section, no parametrized form of the model is necessary. As a result of that, not only parameters like segment lengths, but also the robot's topology can be learned. Therefore the work reviewed in this section does not only address body schema extension, but can cope with more dramatic changes in the robot's body, such as the loss of a limb or a blocked joint, leading to resilient machines. We will focus on two case studies: (1) the work by Sturm *et al.* [83], who show how a robotic manipulator can synthesize and adapt its kinematic model from self-observation and can then use it for reaching; and (2) the work by Bongard *et al.* [97], in which a quadrupedal robot continuously models itself and generates new locomotion patterns.

Let us first point out what the two models have in common. First, both models are explicit in the sense that there is a one-to-one match between the components (e.g. body parts) in the body schema (or model) and their counterparts in the physical robot. The number of joints and body parts presents the prior knowledge. Second, the controllers operate on kinematics (dynamic disturbances are handled by position-controlled servo motors), and only static configurations (i.e. not the dynamics of behavior to reach that configuration) are used to assess the match between the model and the physical robot. Third, both present a case for a 'subjective' schema, as the signals from the robots' own sensors are used to validate the model. And fourth and last, there is a population of candidate models involved.

Let us start with the work of Sturm *et al.* [83]. Here, different robotic manipulators are used (4, 6 and 7 DOF). The robot observes the pose of its body parts (with special visual markers) using an external monocular camera (see Fig. 5). The goal is that the model of the manipulator is learned through exploratory actions and self-observation. In Hersch *et al.* [82] described previously, the parameters of the kinematic chain were learned, providing a coordinate transformation between two sensory modalities - visual (camera) and proprioceptive (joint space). On top of that, different, also classical, approaches to control can be used, and will have to provide a mapping between motor commands and joint angles. Thus, although their body representation could be used for action, it does not contain the motor modality directly. Sturm *et al.*, on the other hand, directly include the action commands. As we will see, their architecture thus also provides a forward and inverse model of the robot (cf. Section II-E).

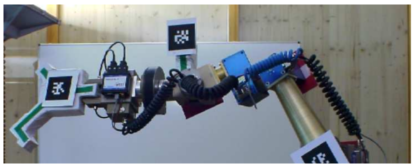
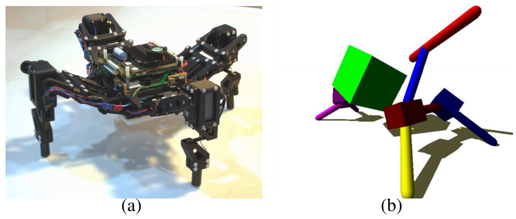


Fig. 5. A 6-DOF robotic manipulator arm learns and monitors its own body schema using an external monocular camera and visual markers. Sturm *et al.* [83]

The body schema in Sturm *et al.* is the joint probability distribution of available actions signals (target angles sent to individual joints), self-observations (as obtained from the camera), and true poses of the body parts (hidden states). The body schema is modeled as a Bayesian network, where the nodes correspond to body parts, action signals and model components. The structure of the network reflects the kinematic chain. For example, the 6D pose of a body part of the manipulator depends on the pose of its predecessor and one of the action signals. These dependencies enter the Bayesian network. The learning problem is then factorized into two parts: First, local models that describe the relationship between pairs of body parts are learned using Gaussian processes regression. Local models that do not explain data well are discarded. Second, a graph is built from the valid local models. Under the assumption that the manipulator has no cycles, the problem of finding the kinematic structure of the manipulator corresponds to the minimum spanning tree of this graph. The cost function is defined as the combination of the marginal data likelihood and a complexity penalty for each local model. Instead of using joint encoders, the relationship between motor commands and positions of the body parts of the manipulator is learned directly, circumventing the mapping between the target motor commands and the angle actually assumed by the joints. In order to control the manipulator, an inverse model is needed, i.e. a mapping from desired pose to action commands. While this can be obtained by searching for the motor commands that maximize the likelihood of generating the desired pose, it results in a high-dimensional optimization problem. Therefore, a different approach is used: the representation of the model allows to apply differential kinematics, in particular, it is possible to compute the Jacobian of the forward model and thus a gradient-descent algorithm is used for selecting suitable motor actions.

In their experiments, Sturm *et al.* demonstrate that: (1) the robot can learn its kinematic model from scratch; (2) the robot can adapt the model to blocked joints as well as to deformations. This presents a solution to automatic model synthesis, calibration, body extension as well as recovery from damage. Furthermore, the model provides additional benefits thanks to its probabilistic nature. First, information from the robot model is combined with the sensory data in a statistically optimal fashion, and the model also contains uncertainty of the estimates. Second, each model candidate has an associated likelihood, and thus multiple candidate models explaining data can be kept in parallel. Classical control, which assumes a single model, can thus be extended to take the uncertainty into account. Third, extending the model in time would allow to perform prediction, or filtering (computing the belief state). Therefore, the Bayesian framework encompasses both long-term (structure and parameters of the network) and short-term body schema (current belief), and a forward and inverse model, including a measure of the reliability of the information.

Bongard *et al.* [97] used a different platform, a quadrupedal robot, whose body schema is to serve the synthesis of locomotor behaviors. Compared to the manipulator arm scenario, the interaction with the environment is much more profound here. A model of the dynamics (mass and inertia) of the robot, as well as of the ground and their interaction (friction model) is indispensable. The robot's self-model is split into two parts here. The first part consists of an externally designed model of the robot and the environment in a physics-based simulator. This is a special form of an explicit model - equations of motion for the mobile robot are not specified analytically, but they are embedded in the physics-based simulator and numerically integrated. This first part of the model contains the robot as a chain of rigid bodies connected by servomotors, and remains fixed during experiments (is "known" to the robot). The second part is the kinematic structure of the robot in the simulator, i.e. how are the rigid bodies connected. This part is unknown to the robot and is subject to learning and adaptation. Fig. 6 shows the real robot and one candidate model (with incorrect kinematic structure) in the simulator. To validate the model the information obtained from the sensors on the real robot is compared with the one from the simulated sensors in the simulator (cf. with the notion of emulator and articulated model of Grush [61] and with mediated model of Marques and Holland [62] in Section II-E).



(a) (b)

Fig. 6. Robot and its (incorrect) candidate model. Bongard *et al.* [97]

A set of 15 candidate self-models is kept. In every (static) configuration of the robot, the sensor readings are taken and compared with the readings from the simulated robot in the same configuration. In [97] only orientation sensors are used, but in [98] more modalities are employed and their relevance is also assessed. However, these configurations - or action that lead to them - are not selected at random. It is the action that is expected to best disambiguate between the candidate models that is executed on the real robot. Behavior synthesis on the model pool thus precedes and only when the information expected to gain is maximum, actions are executed on the real robot. On damage (lower leg part breaks off), a mismatch between the predicted and real sensory signals is detected, and exploration, modeling, and testing is re-initiated until a new model which reflects the change is found.

This architecture also encompasses a forward model. Whole action sequences can be executed in the simulator, and their outcomes observed. New behaviors can thus be synthesized in the model first, which would otherwise be a lengthy process on the real robot. This is an advantage of an explicit model. Unlike an implicit model, which allows to interpolate betwen actuation-sensation patterns that have been seen before, an explicit model allows to extrapolate, and to generate qualitatively new behavioral patterns. Nevertheless, the (explicit) interaction with the environment is very hard to model in this case (e.g., contact modeling with the ground is a notorious problem) and there is always going to be some discrepancy between the model and reality (the reality gap). Although the parameters describing this interaction (such as friction) were fixed in the physics-based simulator and represented prior knowledge in the cited work, in principle, they could also be adaptive.

4) Models including dynamics: Apart from the physics-based simulation used by Bongard *et al.* [97], so far we have dealt with kinematic models only - the forces and torques required to cause a particular motion were not addressed. Nonetheless, these are essential to finally execute an action. This gap is filled by (inverse) dynamics models of the robot or plant. This can be viewed as a relatively independent module and there are indications that a similar strategy is used in biological motor control [59]. Therefore, the models of robot dynamics do not lie at the center of our interest and we refer the reader to many textbooks on the topic, e.g. [79] [73] [80].

Having drawn this parallel between inverse dynamics in biological and robotic motor control, let us also point out the important differences between them. It is probably fair to say that the basis of the field of control in robotics is largely formed by engineered models (e.g. computed-torque control [79] [73]). While model adaptation and dealing with uncertainty is also addressed (by robust and adaptive control [79]), adaptation to dramatic changes in the robot dynamics lies still outside of the scope of these methods. Similarly, the platforms that can be modeled are still largely restricted (mostly stiff rigid bodies). On the other hand, we know that biological motor control can deal with both significant changes to the dynamics or to the kinematics, and with compliant platforms, for instance. Therefore, if we want to deal with such robotic platforms, we may need to resort to implicit models, and this takes us to the next section.

D. Implicit models

This section reviews work where an implicit representation of the robot's body is used. This can take a form of a simple look-up table or it can be a neural network, for instance. We will also review work that deals with self-recognition - how does the robot find its body and separate it from the environment. Finally, we will look at models that address the issue of delays in the effects of robot's actions. Compared to the explicit models, much less prior knowledge enters the implicit representations.

1) Representations of sensorimotor mappings: To derive analytical equations representing the kinematics and dynamics of a controlled system is not always possible. In situations where this is not feasible (in highly nonlinear systems with compliant actuation composed of deformable bodies, for instance), these mappings can still be learned using different function approximation techniques. Such mappings can either aid standard control schemes (as in the case of neural networks for control), or they can be control schemes in their own respect.

If a model of a plant cannot be obtained analytically, it is still valuable to obtain a model that treats the target system as a black-box. Its input-output behavior can be learned by a system identification process. By observing the responses of a system to different inputs a forward model can be learned. For control, however, an inverse model is typically required. This can be either obtained by inverting the forward model (which is possible only in special cases), by directly learning the inverse mapping, or by the so-called distal supervised learning approach [106]. *Inverse kinematics* can be approximated by various approaches: locally weighted regression [107], multilayer perceptrons, or radial basis functions [108], [109]. Over the past decades, connectionist approaches have been integrated into numerous control architectures (for instance model reference adaptive control, model predictive control, internal model control [110]), where they form one or more of the building blocks: plant model, inverse plant model, or controller. One of the earliest architectures that is still being developed is the Cerebellar Model Articulation Controller (CMAC) [111][112]. We will refer the reader to the abundant literature on the topic of neural networks in traditional control schemes [113], [114], [108]. Interestingly, unsupervised (or self-supervised) neural network architectures can also be used. Barreto *et al.* [115] demonstrate the use of self-organizing maps and some of their advantages. For instance, the topological arrangement of network nodes ensures that a redundant manipulator is well-behaved. A 'lazy' cost function is implicitly coded - while looking for an adjacent target point, an adjacent joint configuration is automatically selected.

The big advantage of implicit approaches is that almost arbitrary sensorimotor mappings can be represented. For instance, *inverse dynamics* does not present a problem with different characteristics, assumptions and complexity than inverse kinematics, as is the case with explicit modeling. If dynamic instead of kinematic variables are fed to the learning algorithm, inverse dynamics can be learned in a similar manner (e.g., [116]). Similarly, platforms that were outside of the scope of analytical modeling, such as pneumatically driven robots, can now be treated equally easily [117]. The problems of coordinate transformations and forward modeling do not have to be addressed as separate building blocks anymore.

To further illustrate the case of sensorimotor mappings, let us look at visually guided reaching. This is a hand-eye coordination problem and there are two basic strategies to tackle it: (1) Open-loop control, in which a sensorimotor map that relates the hand visual location and the arm position from proprioception is needed; (2) Closed-loop control, where the visual Jacobian of the manipulator is needed. The open-loop strategy can be realized through a combination of classical explicit frame of reference transformations that involve the hand, body, and camera reference frames. As mentioned in Section III-C2, these maps can be obtained through automated calibration procedures (kinematic chain [88], [89], [90], hand/eye setup [91]). However, a highly structured environment is typically required for these calibration procedures (see [118] for more details). The Jacobian that is needed for the closed-loop strategy (or visual servoing [119]) can be derived analytically, or estimated ([120]).[6] The two strategies, open-loop and closed-loop can also be combined, as demonstrated by Natale *et al.* [118], for instance, where reaching in 3D is possible without prior knowledge of the kinematic model.

The mappings needed to perform visually guided reaching can also be coded implicitly. For instance camera calibration and triangulation can be learned in an implicit manner [121], [122]. Moreover, interestingly, the open-loop component which requires a sensorimotor mapping can be turned into a motor-motor coordination problem, as demonstrated by [99], [100], [123]. Rather than learning the mapping between visual space and arm motor space directly, the eye-head system is exploited. A camera is let to fixate on the target (this can be pre-coded or learned separately) and the appropriate motor variables of the eye-head plant are extracted and used to learn the relationship with the hand motor plant variables that represent reaching to the target. This relationship can be represented by a look-up table [99] or by a self-organizing map [100]. The learned mapping reduces the dimensionality of the problem, and is an instance of a body schema which allows

[6] The Jacobian is a good example that sensorimotor maps can represent relationships between higher-order (in this case first-order since Jacobian is a derivative) variables as well.

TABLE II
BODY SCHEMA TO IMPROVE ROBOT BEHAVIOR - AN OVERVIEW.

Study	Key issue	Platform (S:simulated, R:real)	Body representation
Hersch *et al.* [82]	automatic kinematic chain calibration	humanoid robot (S,R)	kinematic chain
Martinez-Cantin *et al.* [94]	automatic kinematic chain calibration	humanoid torso (S,R)	kinematic chain
Nabeshima *et al.* [95]	body schema extension	humanoid torso (R)	kinematic chain
Bongard *et al.* [97]	body schema acquisition and adaptation	quadrupedal robot (R)	kinematic chain
Sturm *et al.* [83]	body schema acquisition, adaptation and extension	robot arm (S,R)	Bayesian network
Metta *et al.* [99]	body schema development	humanoid torso (R)	look-up table
Gaskett and Cheng [100]	body schema acquisition and adaptation	humanoid torso (R)	self-organizing map
Yoshikawa *et al.* [101]	self-recognition, body image acquisition	humanoid torso (R)	cross-modal map
Gold and Scassellati [102]	self-recognition, agency	humanoid torso (R)	Dynamic Bayesian Network
Natale *et al.* [103]	self-recognition, body schema development	humanoid torso (R)	mutli-layer perceptron
Dearden & Demiris [104]	body schema acquisition	camera and grippers (R)	Dynamic Bayesian Network
Grimes *et al.* [105]	body schema acquisition	walking humanoid (S,R)	Dynamic Bayesian Network

to reach to a certain point in space - the target to which the eyes are looking - in an open-loop fashion. Metta *et al.* [99] also spell out the important features that characterize their approach: (1) the kinematic and dynamic parameters are not explicitly identified as in classical control theory approaches; (2) there is no distinction between the system's calibration and control. In other words, the two processes are completely intertwined, and the performance of the overall system can grow in an incremental fashion over time.

2) Self-recognition: In the works that we have described so far, the goal was to acquire or adapt a body representation. The representation itself has taken various forms - an explicit kinematic chain, a model in a physics-based simulator, or a cluster of implicit sensorimotor mappings. However, it was assumed that a robot knows which signals come from its body. For instance, in the work of Hersch *et al.* [82] or Sturm *et al.* [83] (see Sections III-C2 and III-C3), all the body parts of interest were visible and easy to distinguish. In reality - if we take a developmental perspective and assume that the robot does not have this prior knowledge - the robot first needs to 'find itself' in the stream of sensorimotor signals (cf. Section II-C1).

Yoshikawa *et al.* [101] address the problem of how a robot identifies its arms in a visual image. Unlike objects in the environment, the arms remain at fixed positions, and due to this invariance, they can be extracted from the visual scene and identified as belonging to the body. Hebbian learning is employed to pick up this invariance between the visual modality (disparity after the eyes fixate on an object), and proprioception (position of cameras - pan, tilt). The work of Yoshikawa *et al.* [124] is an extension of this strategy to multiple visual attributes (disparity, luminance, chroma, edges). Since the arms are not allowed to move, the procedure is dominated by perception and we can talk about *acquisition of body image* (cf. Section II-C1).

A largely converse strategy is employed by Fitzpatrick and Metta [125], Natale *et al.* [103], and Gold and Scassellati [102]. It is the active behavior of the robot that is used to self-recognize. Kemp and Edsinger [126] can perhaps be viewed as a transition between the two strategies. The robot's arms are allowed to move, but it is *spatial contingency* - mutual information between salient patches in the visual scene and expectations on appearance and position of the robot's parts - that allows self-recognition. On the other hand, it is *temporal contingency* that is utilized in [125], [103], [102]. The robot learns to recognize its body parts *because* they are moving. However, since external objects can be moving as well, it is the correlation between the visual input (optic flow) and the motor signal that facilitates the body identification [125]. Natale *et al.* [103] improve the robustness of this procedure by using periodic hand motions. Then, the robot's hand could be segmented by selecting, among the pixels that moved periodically, only those whose period matched that of the wrist joints. Gold and Scassellati [102] use probabilistic reasoning and examine the likelihood of three alternative models: (1) robot's own motors generated the movement; or (2) something else generated the movement; or (3) irregular movement. Case (1) would correspond to the robot's own body. Unlike the case of Yoshikawa *et al.*, action plays a key part in these methods. Therefore, it is more appropriate to talk about *body schema acquisition* and *sense of agency* (cf. Section II-C1 again). We also want to point out that this strategy can be naturally extended to action recognition in others and imitation (see [102]), tool use, or interaction with objects (see [103]).

3) Temporal models: We have seen how an agent can exploit temporal contingencies to self-recognize. However, once the agent has found its body, should the temporal domain be still preserved in the synthesis of body representations? The sensorimotor mappings that were discussed so far were largely relationships between various modalities in *static* configurations. Some architectures encompassed a forward or inverse model and thus allowed to iterate a body state in time. However, in reality, different actuators as well as sensors have their specific time delays associated with them. A body schema unfolded in time can be nicely represented with a Dynamic Bayesian Network (DBN). Dearden and Demiris [104] used a similar approach to Sturm *et al.* [83], but included motor delays into the body schema. The problem of model selection among competing candidate body schemata (as represented by the DBN) has thus grown to include the temporal dimension. Hidden states are discrete and represent the states of two grippers (open/closed). Observables are based on optic flow in the visual scene; visual blobs are extracted and clustered with a k-means algorithm. The prior knowledge that enters the body schema is the 'template' for the structure of the Bayesian netwok: from motors to hidden states to observables.

While this approach is more general than Sturm's [83], the toll that needs to be paid is that the system has much fewer DOF (essentially 2).

The work by Grimes *et al.* [105] uses a similar approach, but addresses a different problem: bipedal locomotion. Humanoid walking is a much more difficult problem than robotic manipulation. Balance becomes a key issue, modeling dynamics becomes inescapable, and we have to deal with a floating-base system. Traditionally, explicit modeling is performed based on CAD data, followed by further parameter estimation. The most famous control scheme in use is the zero-moment point (ZMP) control [127]. While this is commonly applied in walking humanoids ([128], [129], [130]), it has not yet been possible to extend it to rough terrain ([131] is an attempt in this direction, but on a quadruped platform). Therefore, Grimes *et al.* [105], instead of using an explicit physics-based model of the robot and a control scheme on top of this, adopted a model-free, or implicit, approach. The kinematic and dynamic states are represented in a Dynamic Bayesian Network (DBN), together with action commands and observables. The problem of balance is addressed by a relationship between sensors (gyroscope and pressure sensors), which is, again, an instance of a subjective or situated body schema. Parameters for the model are learned with Gaussian processes. Implementations with Bayesian networks have the usual benefits that they allow for prediction, planning, or filtering, all that with measures of uncertainty. Moreover, both Dearden and Demiris [104] and Grimes *et al.* have shown how to utilize their architectures in an imitation scenario.

IV. Robots as models of biological body representations

As we have seen in Section II, although direct recordings from the brain have revealed relevant facts about body representations in biology, the mechanisms underlying the working and the development of body schema (and body image) in animals and humans are still far from clear. A difficulty in understanding such mechanisms from the observation of neural activity alone is that it is hard to separate the influence of the target mechanism on the recorded data from a variety of other processes inside the brain, as they result from the interaction among brain, body, and environment. A synthetic approach - investigating the phenomena of interest by implementing them in robots (e.g., [132]) - is a promising methodology to overcome the difficulties that computational neuroscience faces. Not only the mechanisms underlying a mature body schema, but also its development in infants can be addressed by synthetic modeling (Asada et al. [133] provide an excellent review). Body schema implementations that aim at modeling biology naturally feature more biologically realistic architectures and mechanisms. Hebbian learning, self-organizing map (SOM), or spike timing-dependent plasticity (STDP) are often employed. In some cases, it is possible to establish a correspondence between the proposed models and neural firing patterns in the cortex [96], [134]. While it is probably fair to say that this body of research is at its nascent stage, there are a couple of relevant cases that will be described below. The scenarios we will come across will resemble the ones from Section III, but this time, the architectures will not merely draw inspiration from biological body representations, but will explicitly attempt to model the biological mechanisms.

We will structure this section as follows. Many synthetic studies have been carried out to understand multi-modal body representations which, in primates, are found in the parietal cortex. Here, we categorize them into two groups: non-action-oriented body representations (body image), and action-oriented ones (body schema). The former body of work employs cross-modal maps that are modified through Hebbian learning applied on individual modalities [135], [96], [134], [136], [137]. The latter category comprises studies in which the acquired body representations are utilized to coordinate the robot's behavior [138], [139], [140]. Third, we will review the work by Kuniyoshi and Sangawa [141] where the emphasis is placed on the physical interaction between body and environment and on the effect of low-level (spinal) control. On top of these, low-level sensorimotor representations can emerge. The most prominent studies that we will review are summarized in Table III.

A. Non-action-oriented body representations (body image)

Many synthetic studies have focused on how to integrate information from tactile, visual, and proprioceptive sensor spaces. The "body maps" that are acquired are used for recognition of the agent's own body (cf. Section III-D2). Yoshikawa *et al.* [136] focused on correlations in the activation of tactile, visual, and proprioceptive modalities. Through an experience of self-touching, maps linking the modalities were associated by Hebbian learning. While Yoshikawa's study allows to represent only body parts that are visible to the robot, Fuke *et al.* [135] proposed a model in which the invisible parts - the robot's face - can also be incorporated into the body representation. This was done via learning a Jacobian from the motor (joint) space to the visual space. Integrating the velocity, position in visual space can be estimated for invisible parts as well. Then, while the robot was touching its face with the arm, the position in the visual modality could be estimated and matched with the touch modality - learning a cross-modal map. It is then hypothesized that a fetus establishes this correspondence while touching its face in the womb and this may explain why a newborn is able to respond to faces immediately after birth.

Another important topic is body schema adaptation during tool use (see Section II-C3). While we have encountered implementations of this behavior in the section on applications (e.g., [82], [95], [83]), the mechanisms employed were only inspired by biology. The approach of Hikita *et al.* [96], on the other hand, models the mechanisms hypothesized to be used in humans. In particular, they focus on the role of the attention system in detecting body extension by a tool. Based on a neurobiological model by Itti *et al.* [142], a model that enables a robot to detect its own end-effector by associating proprioceptive information with visual information during visual attention, a saliency map, is proposed. Tactile sensation on the robot's hand is used to trigger the association[7]. The representation enables a real robot to recognize its own body and there is an analog to the findings in parietal cortex during use of a tool, as described in [27] (see Figures 7 and 8).

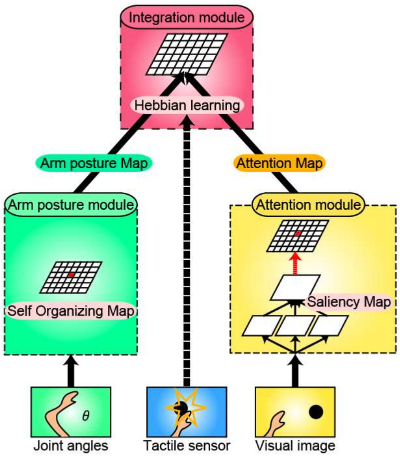
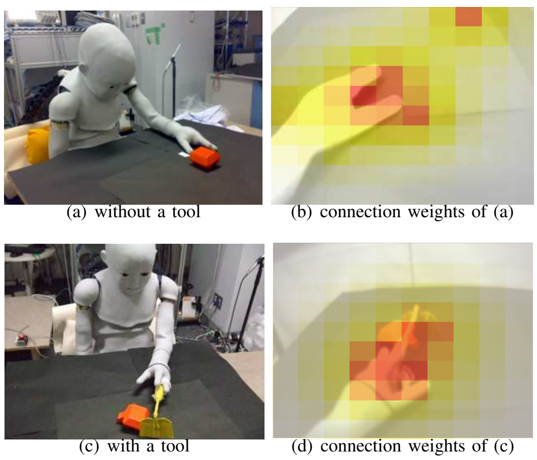


Fig. 7. Overview of the model proposed by Hikita *et al.* [96]. The association between the posture of the robot's arm and position in the visual field is triggered by tactile stimulation. A saliency map makes a robot fixate a point of contact between its end-effector and an object, since more salient features are observed at that point.



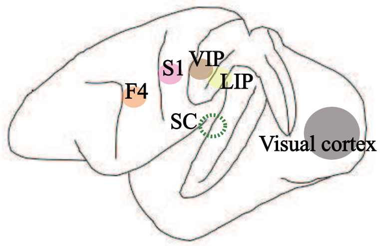
(a) without a tool (b) connection weights of (a)

(c) with a tool (d) connection weights of (c)

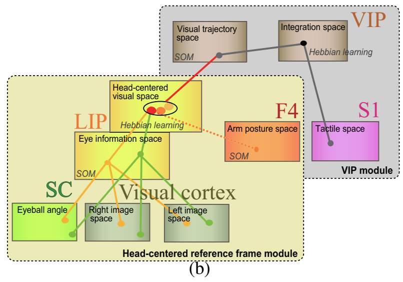
Fig. 8. Body schema extension during tool use. The connection between visual and proprioceptive fields: (a) and (b) without a tool; (c) and (d) with a tool (from Hikita *et al.* [96]). The red areas show a strong connection between visual and proprioceptive spaces in each setting. Confront Fig. 1 for the results from monkeys.

Fuke *et al.* [134] extended the problem of integrating tactile, visual, and proprioceptive modalities by addressing the frame of reference transformation that needs to occur between an eye-centered and a head-centered reference frame. A model

[7]This work resembles the experiments by Nabeshima et al. [95] that we have encountered in Section III-C2. However, unlike Nabeshima, Hikita's work is a more direct attempt at modeling the putative biological mechanisms.



(a)



(b)

Fig. 9. Correspondence between brain regions (a) and representation spaces (b) proposed by Fuke *et al.* [134]. Eye information space is combined with arm posture space into a head-centered visual space. This process bears similarity to connections among F4 and LIP areas. Integration of the head-centered visual space and tactile space produce neural activities similar to the ones observed in VIP area.

was proposed according to the relation between VIP and LIP in human and primate brains as described in Section II-D. Based on studies on infants [15], this integration is assumed to be achieved through hand regard behavior: human infants gaze at their own hands in front of their face at around four months of age. In the experiments of Fuke *et al.* a robot first acquires a head-centered visual space representation by associating ocular angles and camera images while gazing at its hand moving. Then, it integrates tactile sensations with visual stimuli by touching its face. Experimental results with a simulated human-like robot show that the activities of the acquired maps are similar to the ones of the VIP neurons as observed in [47]. The correspondence of the model with brain regions is shown in Fig. 9.

B. Action-oriented body representations (body schema)

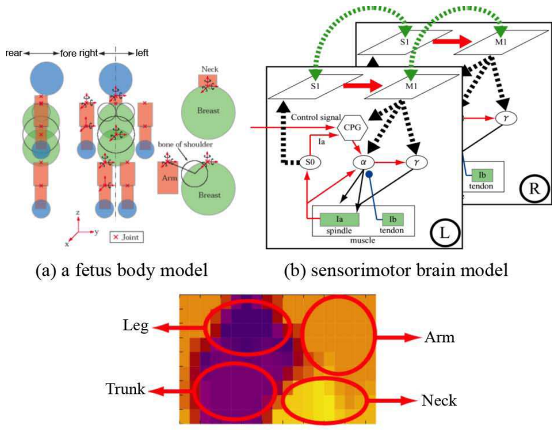
This section deals with models of biological body representations used to guide actions. In some studies, cross-modal maps are first acquired and then exploited to plan the behavior of robots. Morasso and Sanguineti [138] have proposed a model of body schema for motor planning that is presumably carried out in area 5 of the posterior parietal cortex in association with the basal ganglia. The model is called SO-BoS (Self-Organizing Body-Schema) and consists of two components: a sensorimotor mapping (forward kinematic model implemented as a self-organizing cortical map), and inverse sensorimotor mapping (inverse kinematic model implemented as a gradient-descent mechanism in a potential field). The former is first acquired through motor babbling. Then, the latter is tuned depending on the task constraints such as the target position and the posture to reach a target. Results of a simulation of a 3-degree-of-freedom arm show that the proposed model can realize different reaching behaviors that satisfy the constraints. However, the platform used is rather simplistic and the work has a more computational than synthetic modeling flavor.

Stoytchev [143] extended this model to a tool use scenario. An offset vector was added that represented the distance in the visual field from a position of an end-effector to the tip of a tool attached to the end-effector. Results with a simulation of a 2-degree-of-freedom arm showed that the proposed model can extend the body representation and successfully approach a visual target using the tool. The author has also shown that this model can acquire an extended body representation that allows the robot to guide its arm movements through a TV image. The robot detects its own body part based on the synchronization between its own movements and the changes of visual features on the TV screen [139].

Pitti *et al.* [140] have encoded body representations as a spatiotemporal pattern of neural activities in sensorimotor networks. Coordinated behavior, induced by morphological properties, was produced. Spiking neural networks were used to acquire mappings from a log-polar representation combined with a saliency map to motor commands for controlling the neck and the camera's orientation. Connections were regulated by spike-timing-dependent plasticity. Interaction among the body, environment, and the nervous system enabled a robot to self-organize the fixation behavior and the saccade behavior to a salient object. Analysis of the neural activities in the networks revealed a distinction between movement caused by the agent itself and that caused externally, thus representing a sense of agency (cf. Sections II-C1 and III-D2).

C. Development of a low-level body schema

Kuniyoshi and Sangawa [141] investigated the role of tight coupling between a body and its environment and how consistent dynamical patterns can emerge from this close physical interaction. They proposed a model of a neuro-musculo-skeletal system that consists of biologically realistic components such as a skeleton, muscles, spindles, tendon organs, spinal circuits, and medullar circuits (CPGs). On top of that, a basic cortical model from self-organizing maps was constructed. The connections were modulated by Hebbian learning rule during spontaneous movement driven by the activities of the lower circuits. Self-organized body movement was observed in a simple musculo-skeletal model which consisted of two rigid objects connected with a free joint and multiple muscle fibers. This mediated the acquisition of low-level body representations, such as the relations between agonist and antagonist muscles. Further experiments with a human fetal model showed that simple movements, such as crawling and rolling, can emerge. The cortical maps displayed a separation into areas corresponding to different body parts shown in Fig. 10. Related to this work, a real robot that has anthropomimetic features is currently developed in the context of the ECCEROBOT project, where the development of a body schema will be subject to investigation [144].



(a) a fetus body model (b) sensorimotor brain model

(c) mapping from M1 to α

Fig. 10. Low-level body representations in a fetal model (Kuniyoshi and Sangawa [141]) (a) A fetus body model. Its physical properties such as size, mass and joint angle limitations were based on biological findings. (b) Cortico-medular-spinal-muscular model. (c) Self-organizing map from M1 to α, which displayed separation into areas corresponding to different body parts through spontaneous movement driven by the activities of the CPGs.

V. Conclusion and future prospects

The research in cognitive sciences deals with many body representations that are short-term or long-term, conscious or unconscious, perception- or action-oriented. Synthesizing the putative mechanisms behind the biological body representations in robots can serve two goals. First, it can help to endow the robots with new capabilities that are ubiquitous in nature, yet unattainable by the machines of today. Second, synthetic modeling, i.e. investigating hypothetical mechanisms in artificial brain-body-environment systems, can complement empirical studies of psychology and neurosciences. These two avenues have been the subject of the present review.

To this end, we have first presented a review of the treatment of body representations in cognitive sciences. However, our survey was biased by having a robotic implementation in mind. Body representations in robots cover only a subspace of their biological counterparts so far. They can be long-term or short-term, but they can hardly be considered conscious and they are largely action-oriented (since we are usually interested in the robots performing some task). Therefore, we have largely neglected the phenomenological, or reflective, mechanisms of body representations, but concentrated on more low-level, pre-reflective, computational mechanisms such as plasticity of body representations, or coordinate transformations. We have explicitly attempted to clarify the relationship between the closely related notions of body schema, body image, peripersonal space and forward models.

To have a model of a robot in order to control it comes naturally to most control engineers and roboticists. A model

TABLE III
MODELS OF BODY REPRESENTATIONS IN BIOLOGY - AN OVERVIEW.

Study	Key issue	Platform (S:simulated, R:real)	Body representation
Yoshikawa *et al.* [136]	body image acquisition, multimodal representation	humanoid torso (R)	cross-modal map
Fuke *et al.* [135]	body image acquisition, extension to invisible body parts	humanoid torso (S)	self-organizing maps
Fuke *et al.* [134]	body image acquisition, coordinate transformations	humanoid torso (S)	self-organizing maps
Hikita *et al.* [96]	body image/schema acquisition and extension, self-recognition	humanoid torso (R)	self-organizing maps
Morasso & Sanguineti [138]	body schema acquisition	robotic arm (S)	self-organizing body schema
Stoytchev *et al.* [143], [139]	body schema acquisition and extension	robotic arm (S,R)	self-organizing body schema
Pitti *et al.* [140]	body schema acquisition, self-recognition, agency	robotic head (R)	spiking neural networks
Kuniyoshi & Sangawa [141]	low-level body representations	humanoid (S)	self-organizing maps
Marques *et al.* [144]	low-level body representations	humanoid (R)	–

of a plant (or robot) indeed is a representation that is used to guide the robot's actions and can thus be considered a kind of body schema. However, such a model has very different characteristics from those of a biological body schema: typically it is fixed, explicit, precise, centralized, and objective. These very characteristics of a classical model of a plant restrict the domains in which robots can be successfully used to very limited, precisely controlled environments. There are also costs associated with the development of such a model. Therefore, it is desirable that robots can develop, calibrate and adapt their models automatically. We have reviewed work that departs from the traditional field of robotics and extends it toward online automatic self-calibration. Beyond self-calibration, architectures that can also cope with topological changes have been analyzed, paving the way for the adaptive and the resilient machines of the future. Apart from body representations that have an explicit nature, the body schema of a robot can also be represented in an implicit manner. While this traditionally meant a connectionist (neural network) implementation, models using Bayesian networks are gaining popularity.

Both, explicit and implicit representations, have their pros and cons. Explicit models typically require more input from the designer - a parametrized kinematic model, or at least number and characteristics of joints, for instance. On the other hand, what they offer in return, can be possible integration with traditional control schemes, extrapolation to previously unseen configurations, or easier debugging. A representation that has an analytical form is also more compact and has an infinite resolution compared to a look-up table or self-organizing map that stores previously seen sensorimotor relationships only. The biggest merits of implicit representations probably are that little prior knowledge is required, and even problems that are outside of the scope of analytical treatment (e.g. deformable bodies) can be tackled. Calibration of sensorimotor mappings and their employment in control can be intertwined.

The mechanisms underlying the working and development of body schema (and body image) in animals and humans are still far from clear. Uncovering them has been largely the task of neuroscience. Many findings were obtained by direct recordings from brain. However, even though the recording/imaging techniques are improving, there are still a lot of difficulties associated with "live" recordings from experimental subjects. Empirical studies have been supplemented by computational modeling. However, in many situations, a whole brain-body-environment system is indispensable. This is where robots and simulated robots come into play as tools to investigate biological body schema. While it is probably fair to say that many of the results are still preliminary, there are several relevant cases that we have reviewed.

We want to conclude by identifying the trends and also the weak spots in the research that we have just summarized and also propose areas for future research. First, the work on models in robotics is heavily biased toward manipulator arms, observed by a camera (cf. "humanoid torso" in Tables II and III). At the same time, the platforms are typically very stiff. This holds not only for traditional, but also for bio-inspired research. Therefore, a future research challenge is to deal with other behaviors and platforms: locomotion and compliant robots, for instance. Second, the integration of multiple modalities as demonstrated by biological agents, is still largely lacking - visual modality is often the only one that complements proprioception (joint angles). Third, next to traditional analytical methods from control theory and connectionist models, Bayesian networks are becoming a prominent tool to represent a body schema, with the additional benefits of integrating uncertainty in them. Fourth, most of the research discussed is demonstrated to work in rather simple scenarios (limited number of degrees of freedom, for instance). The extent to which the individual solutions can be scaled up is an open question.

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Appendix C

Perception, motor learning, and speed adaptation exploiting body dynamics: case studies in a quadruped robot

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Perception, motor learning, and speed adaptation exploiting body dynamics: case studies in a quadruped robot

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Abstract: Animals and humans are constantly faced with a highly dimensional stream of incoming sensory information. At the same time, they have to command their highly complex and multidimensional bodies. Yet, they seamlessly cope with this situation and successfully perform various tasks. For autonomous robots, this poses a challenge: robots performing in the real world are often faced with the curse of dimensionality. In other words, the size of the sensory as well as motor spaces becomes too large for the robot to efficiently cope with them in real time. In this paper, we demonstrate how the curse of dimensionality can be tamed by exploiting the robot's morphology and interaction with the environment, or the robot's embodiment (see e.g., [1]). We present three case studies with underactuated quadrupedal robots. In the first case study, we look at terrain detection. While running on different surfaces, the robot generates structured multimodal sensory information that can be used to detect different terrain types. In the second case study, we shift our attention to the motor space: the robot is learning different gaits. The online learning procedure capitalizes on the fact that the robot is underactuated and on a "soft" control policy. In the third case study, we move one level higher and demonstrate how - given an appropriate gait - a speed adaptation task can be greatly simplified and learned online.

Keywords: legged robot, terrain detection, locomotion learning, speed adaptation, body dynamics

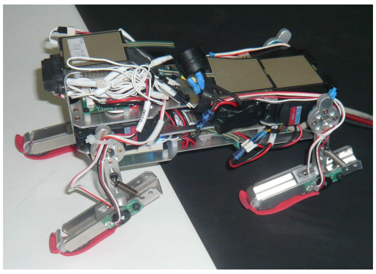

Fig. 1 **Quadruped robot used in case studies 1, 2.** A total of 12 sensors from 4 modalities (4 pressure sensors on feet, 4 angular sensors in passive knee joints, 3 acceleration sensors, and 1 infrared sensor) were used.

1. EXPERIMENTAL SETUP

We have used two underactuated quadrupedal robots in our case studies. They had four identical legs driven by position-controlled servomotors in the hips. The 'knees' were passive and had springs attached. The mechanical design (the weight distribution, proportions, springs used etc.) is a result of our previous research [2]. The robot used in the first two case studies can be seen in Fig. 1.

2. CASE STUDY 1: TERRAIN DETECTION

The first case study dealt with perception, in particular terrain classification. In mobile wheeled robots, this problem is typically solved through fusion of several several distal, i.e. non-contact, sensors (e.g., cameras, laser range finders), followed by supervised classification into traversable vs. non-traversable terrain. Sensing using non-contact sensors has the obvious advantage that information is available ahead of time. On the other hand, such sensors deliver information relevant for traversability in a very indirect manner. Therefore, we have decided to follow an alternative strategy: we want to profit from a full-fledged interaction of the robot with the ground. Following the approach of Lungarella and Sporns [3], who studied how active generation of multimodal sensory stimulation delivers structured sensory information, we have employed information-theoretic methods (mutual information and transfer entropy) that explicitly compare not only sensory but sensory-motor information structure generated by the robot running on different grounds.

3. CASE STUDY 2: LEARNING GAITS

In case study two, we have shifted our attention to the problem of motor learning. The state of the art in robotics can be characterized by two different streams. The first, "traditional", stream employs control laws that prescribe trajectories to the robot's body and the legs and then enforce them using stiff, high-power, actuation. A model of the robot's forward and inverse kinematics and/or dynamics is required. The robot is then capable of precisely executing arbitrary trajectories, picking specific footholds for instance. A good example is the Little Dog [4]. The second "stream" draws inspiration from biology, following the observation by Marc Raibert that the brain does not control the body, but makes suggestions only. The goal is not to override the complex dynamics of the body in the environment but rather exploit it and channel it in particular directions. This strategy results in simplification of central control and greater energy efficiency. Pfeifer et al. [1] provide an overview. We have also conducted studies in a similar vein [2] that gave rise to the quadruped platforms used in this study. Nevertheless, the robots coming out of these studies still lack the versatility of the robots that follow the ”strong control“ paradigm - they are often restricted to a single gait (an extreme example being the passive dynamic walkers).

In this case study we have conducted preliminary experiments in online learning of different gaits in our underactuated quadruped platform. We use online optimization (simulated annealing - SA) to acquire signals for four active joints of the robot. By taking advantage of the symmetries of the body, we managed to reduce the dimension of the parameter space to mere 7 parameters - to our knowledge, this is extremely low - for instance, Chernova and Veloso [5] faced 54 dimensions in the AIBO robot. We have successfully learned gaits for different speeds and also some turning gaits. Typically, tens of iterations of the SA algorithm (with 30 seconds per iteration, for instance) were required to learn a gait. Videos of the gaits will be shown at the conference.

This case study demonstrates that learning is possible in real time. This follows from the underactuated nature of the robot and the ”soft” control policy. It is not only the number of actuated degrees of freedom that is responsible for the shrinking dimensionality; it is also the control “philosophy“. Whereas in the AIBO or Little Dog the trajectory of the legs as well as the body is parametrized, in our case, we prescribe signals to the actuators only - everything else (e.g. COM trajectory) is emergent from the interplay of the actuators, the body, and the environment.

4. CASE STUDY 3: SPEED ADAPTATION

In our third case study, we closed the perception-action loop and studied a feedback control scenario. The robot equipped with an ultrasonic distance sensor should keep a fixed distance from the treadmill end and respond to changes of speed of the running belt and to changes of the target distance. The difficulty of the task largely depends on the complexity of speed modulation in the robot. We have developed a bounding gait in which the speed can easily be controlled with a single paramater - frequency of all legs. Moreover, the relationship between the frequency and the resulting speed of the robot was linear and the gait covered a big range of speeds, from 4 to 28 cm/s (or 0.25 to 1.7 of robot’s length). The task could then be accomplished with a simple proportional-derivative (PD) control of a single parameter: frequency. The controller was tuned by an online parameter search for the P and D gains using the simulated annealing algorithm. A sample of the performance is depicted in Fig. 2.

We have shown how the speed adaptation task in a legged robot can be simplified to the maximum and hence learned online. Let us analyze the components that are responsible for this behavior. First, the characteristics of

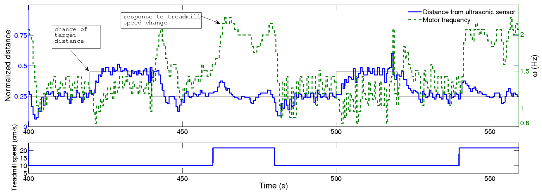

Fig. 2 **Speed adaptation performance.** The top graph shows the target (target distance - black line) tracking performance by the robot (actual distance measured by sensor in blue; distance had a range 10-90 cm and was normalized). When the target moves, the robot needs to respond with an appropriate change in frequency (green dotted line). The same applies when the treadmill speed (bottom graph) changes.

the gait - linear relationship of frequency to speed plays a key part. Second, the optimization algorithm has come up with a high gain controller, which allows for quicker responses and better tracking performance. However, it also results in oscillations of the control parameter (cf. Fig. 2, top). Interestingly, the system could absorb the large perturbations. We hypothesize that this was possible due to mechanical self-stabilization of our system [2]. Third, the fact that a new control parameter can be introduced at any time further simplifies the situation and allows for quicker responses.

5. ACKNOWLEDGMENTS

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Appendix D

Bootstrapping perception using information theory: Case study in a quadruped robot running on different grounds

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BOOTSTRAPPING PERCEPTION USING INFORMATION THEORY: CASE STUDIES IN A QUADRUPED ROBOT RUNNING ON DIFFERENT GROUNDS

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Animals and humans engage in an enormous variety of behaviors which are orchestrated through a complex interaction of physical and informational processes: the physical interaction of the bodies with the environment is intimately coupled with informational processes in the animal's brain. A crucial step toward the mastery of all these behaviors seems to be to understand the flows of information in the sensorimotor networks. In this study, we have performed a quantitative analysis in an artificial agent - a running quadruped robot with multiple sensory modalities - using tools from information theory (transfer entropy). Starting from very little prior knowledge, through systematic variation of control signals and environment, we show how the agent can discover the structure of its sensorimotor space, identify proprioceptive and exteroceptive sensory modalities, and acquire a primitive body schema. In summary, we show how the analysis of directed information flows in an agent's sensorimotor networks can be used to bootstrap its perception and development.

Keywords: information theory; transfer entropy; perception; developmental robotics; sensorimotor contingencies; body schema;

1. Introduction

Animals are constantly being confronted with a massive multidimensional flow of information that is sampled by their receptors and, after some preprocessing, relayed to their brains. This information has to be processed for the animal to be able to take the right decisions and execute the actions that maximize its chances of survival. In addition, the organism and the environment are dynamically and reciprocally coupled and so are the sensory and motor signals. It is the sensorimotor networks (as opposed to purely sensory information) and the dynamic patterns that exist in them that provide the basis for further processing. Cognition is then best viewed as emerging from this dynamic sensorimotor coupling (e.g. [39, 26]).

The view just described holds for natural and artificial agents (i.e. animals and robots) alike. Robots - if they are to autonomously succeed in the real world - also need to extract the relevant information about their interaction with the environment. In order to understand the nature of the processing that is responsible for cognition, the prerequisite seems to be to quantify and analyze the structure of the information flow in these sensorimotor networks. The tools of information theory such as entropy, mutual information, integration, complexity and transfer entropy have proven useful in this respect. They have been applied to inspect information flows inside the brain (e.g. [8, 37, 11, 9]), as well as in the data collected from robots. Lungarella and Sporns [20] have conducted studies on robots that illustrate the effect of individual components of the sensorimotor loop on the information structure. In particular, they showed how a given sensorimotor coordinated behavior (such as foveation) can increase the information content that reaches a given sensor (an artificial retina). Manipulating the sensor morphology (log-polar transformation in this case) showed similar effects. Williams and Beer [41] conducted an information-theoretic analysis of a simple agent engaged in a categorization task. Nakajima et. al. [22] showed how directed information flow, measured by symbolic transfer entropy can help to characterize the force-propagation in an artificial octopus arm.

The bulk of the work described so far was adopting a largely descriptive perspective - given a behaving system (a brain, or a complete agent with sensors and actuators), the information flow and structure was analyzed. We have argued above that this is a key step to understand the behavior of the system. However, an alternative perspective is to look at the world through the eyes of the agent itself. Imagine an animal or robot has just been "born". Using its actuators, it can interact with the world, generating sensory stimulation. Without prior knowledge of its body, sensory apparatus, and the surrounding environment, how can it make sense of the sensorimotor signals it is experiencing? As the agent interacts with the environment, it will experience some patterns (regularities, contingencies) much more often than others - this is given by the agent's embodiment, the morphology and material properties of its body and the placement of its sensors ([14] provide an overview of case studies illustrating these effects). Remembering or representing those regularities will be useful to the agent. But where should the agent start? We think that it should start at the very basis: it should first learn the extent of its body, the things it can influence and what lies beyond its control and should be attributed to the environment.

Such a process has been observed in infants who spend substantial time in their early months observing and touching themselves [33]. Through this process of babbling, intermodal redundancies, temporal contingencies, and spatial congruences are picked up. In such a process, the infant forms a model of its body (a body image or body schema, see e.g. [4, 3, 21]). A developmental approach can also be applied to robots [19, 40, 27]. To identify its own body and learn about its contingencies is a natural candidate to start the autonomous development in an artificial agent (see [13] for a review on self-models and their acquisition in robots). Several studies along those lines have been conducted: typically, they involve an upper torso humanoid robot that is observing the space in front of it with a camera. The goal is to identify the parts of the visual scene that belong to its body (its arms, for instance). Different assumptions can be employed: the robot is static and environment is varied [43], or, on the contrary, temporal contingency is exploited by the robot - the robot learns to recognize its body parts by moving them [7, 23, 10]. Some researchers attempt to start with even less prior knowledge: Olsson et al. [24, 25] and Philipona et al. [30] study cases, where the agent is confronted with raw uninterpreted sensory signals only. There is no preprocessing, no knowledge of geometry and the agent does not even know which signals come from which modality. In [30] a simple simulated agent learns to make the distinction between body and environment by observing over which part of the sensory channels it has complete control. Olsson et al. [24, 25] have collected data from a real robot and showed that using an information metric as distances between the sensory and motor channels, the robot is able to reveal the (mainly spatial) relationships from its morphology (eg. arrangement of camera pixels).

Our work is very much in line with the approach of Philipona et al. [30] and Olsson et al. [24, 25]. For our study, we have chosen a running quadruped robot with the following modalities: four motor signals, eight angular position sensors (4 on active and 4 on passive joints), 4 pressure sensors on the robot's feet, a 3-axis accelerometer and 3-axis gyroscope. The control signal and the environment (five different ground materials) are systematically varied and the sensorimotor data is collected. The information flows are analyzed using transfer entropy and the effect of the different conditions is investigated. Then, we adopt the perspective of the autonomous agent and show how the agent can use the information flows to: (1) derive a primitive body schema and infer the controllability of different sensory variables; (2) discriminate different environments; (3) discover the structure of its sensorimotor space (identify proprioceptive and exteroceptive modalities, group different modalities and extract topological relations); and (4) interpret the quantity of information flow to assess the utility of different sensory channels and its overall performance.

This article is structured as follows. In Sec. 2, we will first introduce the information theoretic methods used and the experimental setup. In Sec. 3, we report on the results of the experiments. A brief section desribing the robot's behavior from an observer perspective is followed by a detailed analysis of the information flows under different conditions and their implications for the robot's autonomous development and perception. The paper is closed by a discussion, followed by a final conclusion and suggestions on future work.

2. Materials and Methods

In this section, we describe the information theoretic measures used, our experimental setup, and explain in detail how we analyzed the data in this paper.

2.1. *Information Theoretic Measures: The Transfer Entropy*

We use the term information in the Shannon sense, that is, to quantify statistical patterns in observed variables. Thus, the measures presented here are based on Shannon entropy [2]. Given a time series x_t from the system X, entropy $H(X)$ provides a measure of the average uncertainty, or information, calculated from the probability distribution $p(x_t)$ according to:

$$H(X) = -\sum_{x_t} p(x_t) \log p(x_t). \tag{1}$$

The association between two time series is often expressed as their mutual information

$$I(X;Y) = \sum_{x_t} \sum_{y_t} p(x_t, y_t) \log \frac{p(x_t, y_t)}{p(x_t)p(y_t)}. \tag{2}$$

which expresses the deviation from the assumption that both are independent from each other. However, mutual information also contains information that is shared by X and Y due to a common history and it is invariant under exchange of the two variables. As we were interested in characterizing the directed information flow between the time series, we used *transfer entropy* [34], which provides this directionality and removes the shared information. Transfer entropy was introduced to measure the magnitude and the direction of information flow from one element to another and has been used to analyze information flows in real time series data from neuroscience [9, 11], robotics [38, 22], and many other fields. Given two time series X and Y, the transfer entropy TE essentially quantifies the deviation from the generalized Markov property $p(x_{t+1}|x_{t-\tau}) = p(x_{t+1}|x_{t-\tau}, y_{t-\tau})$ [34]. If the deviation is small, then $Y_{t-\tau}$ can be assumed to have little relevance on the transition from $X_{t-\tau}$ to X_{t+1}. If the deviation is large, however, then $Y_{t-\tau}$ adds information about the transition of $X_{t-\tau}$ and the generalized Markov property is not valid. The deviation from this assumption can, similar as in the mutual information, be expressed as a specific version of the Kullback-Leibler divergence:

$$TE_\tau(Y \to X) = \sum_{x_{t+1}} \sum_{x_{t-\tau}} \sum_{y_{t-\tau}} p(x_{t+1}, x_{t-\tau}, y_{t-\tau}) \log \frac{p(x_{t+1}|x_{t-\tau}, y_{t-\tau})}{p(x_{t+1}|x_{t-\tau})} \tag{3}$$

where the sums are over all possible states, t is the current time step and $\tau \in \mathbb{N}_0$ indicates the time lag of the transition.

In other words, TE measures how well we can predict the transition of the system X by knowing the system Y, beyond the degree to which X already disambiguates its own future. Transfer entropy is non-negative, any information transfer between the two variables resulting in $TE \geq 0$.

As proposed by Williams & Beer [42], the transfer entropy can be decomposed in two different *kinds* of information transfer, the *state-dependent transfer entropy* ($SDTE$) and the *state-independent transfer entropy* ($SITE$). The former characterizes the information transfer that is caused by the *synergy* of both variables in predicting the transition from $X_{t-\tau}$ to X_{t+1}, so it not only depends on $Y_{t-\tau}$, but also on the state of $X_{t-\tau}$. The latter kind of information transfer is the *unique information* that $Y_{t-\tau}$ yields about X_{t+1} and is completely independent from $X_{t-\tau}$. Moreover, in control theoretic terms the $SITE$ expresses the open-loop controllability of a variable X by its controller Y, while the $SDTE$ expresses the Y's closed-loop controllability of X [42].

The state-dependent and state-independent transfer entropy are defined as

$$SITE_\tau(Y \to X) = I(X_{t+1}; Y_{t-\tau}) - I_{min}(X_{t+1}; Y_{t-\tau}, X_{t-\tau}) \tag{4}$$

$$SDTE_\tau(Y \to X) = I(X_{t+1}; Y_{t-\tau}, X_{t-\tau}) - I_{max}(X_{t+1}; Y_{t-\tau}, X_{t-\tau}) \tag{5}$$

$$TE_\tau(Y \to X) = SITE_\tau(Y \to X) + SDTE_{\tau_x}(Y \to X) \tag{6}$$

where I_{min} is defined as:

$$I_{min}(X_{t+1}; Y_{t-\tau}, X_{t-\tau}) = \sum_{x_{t+1}} p(x_{t+1}) \min_{R \in \{Y_{t-\tau}, X_{t-\tau}\}} I(X_{t+1} = x_{t+1}; R) \tag{7}$$

and I_{max} is defined the same way except substituting min with max.

In order to remove the bias due to the statistical properties of the time series, and in order to make the information transfers between different signals comparable, we subtract the shuffled information transfer and normalize it to the range $[0, 1]$ according to [11]. The shuffled information transfer is calculated by first scrambling the data of the time series Y so that the time-dependency is lost but the statistical properties remain. The normalized transfer entropy is then expressed as:

$$TE_\tau(Y \to X) = \frac{TE_\tau(Y \to X) - TE_\tau^{shuffled}(Y \to X)}{H(X_{t+1}|X_{t-\tau})} \tag{8}$$

2.2. *Experimental Setup*

The experimental setup was identical to our previous work [32]. We recapitulate it here for the reader's convenience.

2.2.1. *Robotic Platform and Control Signals*

The robot used (*Fig.* 1 (a)) had four identical legs driven by position-controlled servomotors in the hips. It had passive compliant joints at the knees. Upper and lower limb were connected with springs. A special material (adhesive skin used for ski touring from Colltex), which has asymmetrical friction properties, was added onto the robot's feet. This allowed the robot to get a good grip during leg retraction (stance), and enabling sliding during protraction (swing). The mechanical design (weight distribution, proportions, springs used, etc.) was a result of previous research (e.g. [16]).

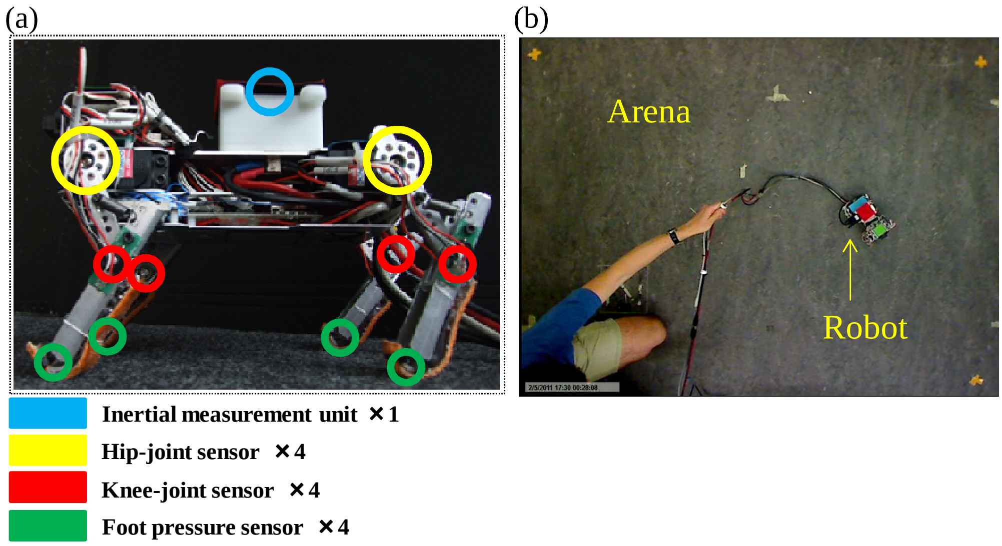

Fig. 1. **Robot experiments. (a)** The quadruped robot "Puppy" with its set of sensors (colored circles). **(b)** The arena used in the experiments (linoleum ground shown). The picture was taken from an overhead camera which was used to track the robot trajectories.

We prepared three sets of position control commands for the servomotors, resulting in three distinct gaits. The first one was the *random* gait, where the target hip joint angle for each leg was set randomly with certain smoothing constraints (to avoid too high frequencies that would exceed the motor bandwidth). The remaining two gaits were based on a simple oscillatory position control of the motors, each motor signal a sine wave. The target hip joint angle γ_i of each motor i (and hence of each leg) was determined as

$$\gamma_i(t) = \alpha_i \cdot \sin(2\pi f t + \theta_i) + \beta_i, \tag{9}$$

where the oscillation was varied by changing the amplitude α_i, offset β_i, frequency f, and phase lag θ_i parameters. Offset β_i defines the center of the oscillation. In the experiments reported here, frequency f of all legs was set to 1 Hz. By experimentation, we have prepared two parameter settings which gave rise to two turning gaits. The *bound right* gait was derived from a bounding gait; the *turn left* gait achieved the left turn by simply using a higher amplitude in the hind right leg. The motor signals of the three gaits are shown in *Fig.* 2.

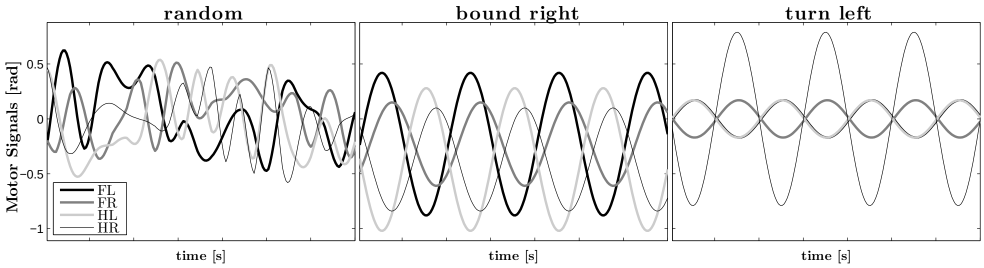

Fig. 2. **Motor time series.** The plots show 3.5 s of the motor commands as the robot runs with *random*, *bound right* and *turn left* gait respectively. The signals are shown for every leg, *FL*: front left, *FR*: front right, *HL*: hind left, *HR*: hind right.

Besides the four motor channels (denoted as M_{FL},M_{FR},M_{HL},M_{HR}), we used 18 sensory channels from the robot (see *Fig.* 1 (a)). Eight potentiometers were used to measure the joint angles, four on the active hip joints (H_{FL},H_{FR},H_{HL},H_{HR}) and four on the passive knee joints (K_{FL},K_{FR},K_{HL},K_{HR}). On the robot's feet were four pressure sensors (P_{FL},P_{FR},P_{HL},P_{HR}). Linear accelerations in three axes (A_X,A_Y,A_Z) and angular velocities around the three axes (G_X,G_Y,G_Z) were taken from an inertial measurement unit (IMU). All sensory data were sampled at 50Hz. For convenience, we refer to the hip and knee angular sensors as "hips" and "knees" and speak about "motors" when we mean the motor commands.

2.2.2. *Arena and Ground Conditions*

During the experiments, the robot was running in an arena roughly 2.5 x 2.5 m and was tethered[a] (*Fig.* 1 (b)). The turning gaits were chosen to keep the robot inside the arena. To investigate the effect of ground conditions, we used five different ground materials: *linoleum*, *foil*, *cardboard*, *styrofoam* and *rubber*. The main difference was in the friction coefficient between the ground material and robot's feet[b] In addition, the *rubber* and *cardboard* contained regular ridges.

2.2.3. *Experiments*

As we have discussed in Sec. 1, behavior is an outcome of the dynamical reciprocal coupling of the brain, body and environment. *Fig.* 3 illustrates this schematically. All the interacting components introduce some constraints on the interplay and

[a]Cables were used for data transfer and power transmission. Although they did affect the robot's dynamics, an effort has been made to minimize these effects by carrying the cables by the experimenter.

[b]We estimated static friction coefficients by putting a block covered with the same adhesive skin as on the robot's feet on inclined planes covered with the different ground materials. As the adhesive skin has asymmetrical properties, two values were obtained for each material. The low/high values were: *linoleum*: 0.31/0.40, *foil*: 0.39/0.39, *cardboard*: 0.64/1.10, *styrofoam*: 0.74/1.06, *rubber*: 0.76/0.91.

together induce some regularities or structure. Adopting the situated perspective, we will study how much can be inferred by the agent about the interaction from observing the sensorimotor flows only. To this end, we have designed experiments in which two of the interacting components are systematically varied.

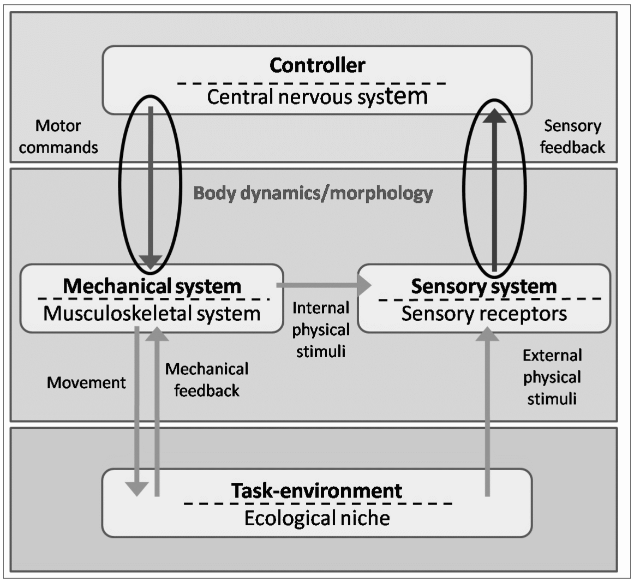

Fig. 3. **The interplay of information and physical processes.** Driven by motor commands, the mechanical system of the agent acts on the external environment (different ground substrates in our case). The action leads to rapid mechanical feedback (for example, springs in the passive knees are loaded). In parallel, external stimuli (pressure on the robot's feet or acceleration due to gravity) and internal physical stimuli (bending of joints) impinge on the sensory receptors (sensory system). The arrows marked with ellipses correspond to the information flows that are available to the agent's "brain" for inspection; these are the subject of our analysis. Figure and text adapted from [29].

Experiment 1: *Varying the controller.*

We have varied the control signals sent to the robot's motors, which give rise to disctinct gait patterns. A set of random signals (*random*) and two coordinated motor controllers (*bound right* and *turn left*) were prepared. Keeping the body and environment constant (*linoleum* ground was used), we investigated how the information structure changes with the different controllers.

Experiment 2: *Varying the environment.*

By fixing the controller to the *bound right* gait, we investigated how the ground conditions affect the informational structure experienced by the robot. For the ground conditions, we used *foil*, *linoleum*, *cardboard*, *styrofoam* and *rubber*.

The body was not varied in our experiments. However, as the other main actors - the control signals and the environment - were systematically manipulated, it was to some extent possible to investigate its effect by uncovering the invariant (always present) structure in the sensorimotor space.

2.3. *Data Analysis*

The trial durations of the experiments were between 60 and 130 seconds. To have an equal number of samples for the calculations of the information transfer, we divided longer trials into subtrials of 58s length (2900 samples). Additionally, we discarded the first 2 seconds (100 samples) of each trial, in order to exclude the data of the transition from sitting to running. This way we obtained between 2 and 5 subtrials per condition. The marginal and joint probability distributions that were needed to calculate the information flows were estimated using histograms. After normalizing the time series to a standard normal distribution ($X, Y \sim \mathcal{N}(0, 1)$), the state space was divided into 20 equally spaced bins ranging from [-4, 4] and the frequency of each state was counted. We tried different bin numbers (5 to 64) and ranges and observed no qualitative difference in the resulting information transfer. The information transfer was then averaged over all trials in each condition. We calculated them for time lags $\tau = [0, 1]$ seconds (1 second was the period of locomotion of the robot) and selected the maximum across $\tau = \text{argmax}_\tau \, [TE_\tau(Y \to X)]$. The shuffled information transfer used for the normalization was calculated by scrambling the time series of Y 100 times, then calculating the information transfer for all 100 scrambled time series and taking the mean of that.

3. Results

In this section, we start by briefly looking at the behavior of the quadruped robot in the arena from an observer perspective. Then we will analyze the information structure that can be extracted from the time series. We will see how the behavior is reflected in the information structure and how it can contribute to the robot's perception and development. We also would like to draw the reader's attention to a video from the experiments that will provide a clearer picture of the experimental conditions in which the robot interacts with its environment: `https://files.ifi.uzh.ch/ailab/people/hoffmann/videos/ACS2012/SchmidtEtal_ACS_2012_accompVideo.mpg` or `.wmv`.

3.1. *Behavior*

Fig. 4 (a) compares example trajectories of the robot for the three different gaits on the *linoleum* ground. We can clearly see that the robot's behavior was different in each gait. Interestingly, we found that for the *random* gait the robot moved forward and had a tendency to turn clockwise (light gray line). Since the motor signal was random, we attribute this pattern to the asymmetry in the morphology of the robot. The forward motion can be attributed e.g. to the mass distribution, the leg shape, and the asymmetric friction properties of the adhesive skin on the robot's feet. The turning effect could be explained by the IMU attachment with the cable pointing to the right. In the *turn left* gait, the trajectories of the robot showed counterclockwise circles (dark gray line). From the pronounced "zig-zag" shape - as seen by the overhead camera - we can also observe that the robot's rolling motion was substantial and larger than the forward motion of the robot in each locomotion period. In the *bound right* gait, the robot turned clockwise (black line). The diameter of the trajectory seemed to be modulated by the ground type (*Fig.* 4 (b)). In particular, if the friction between ground and feet was larger, the diameter of the circle was smaller. In summary, the robot showed a characteristic behavior for each gait condition (controller) and its behavior is strongly affected by the ground type (environment).

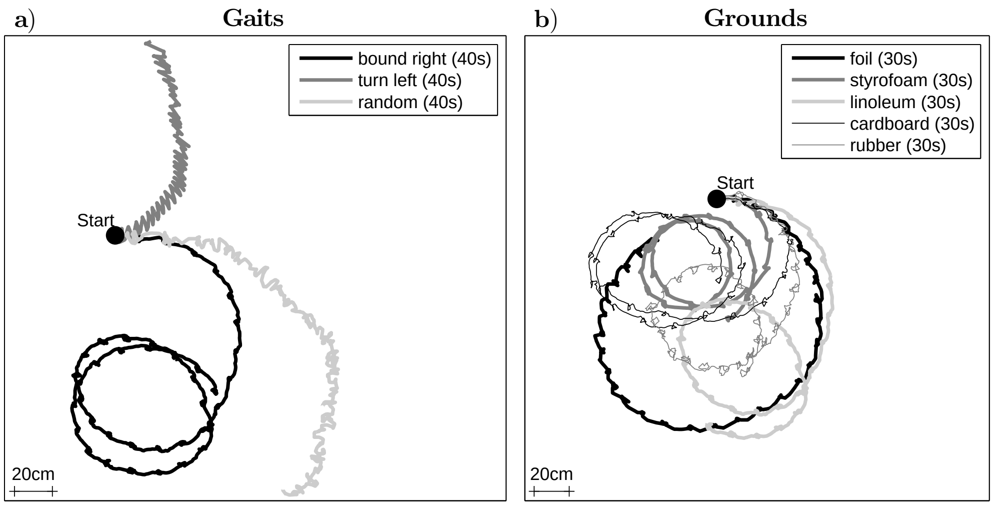

Fig. 4. **Robot trajectories.** Typical trajectories of the robot's center of mass in the arena, as viewed from above. **(a)** The trajectories on the *linoleum* ground when running with *bound right* (black), *turn left* (dark gray) and *random* (light gray) gait. **(b)** The trials from different grounds with the *bound right* gait. The trajectories also reveal how the turning radius and the distance traveled (the speed of the robot) was dependent on the ground condition.

3.2. *Experiment 1: Influence of the Controller on the Information Structure*

3.2.1. *The Random Controller and Body Schema Synthesis*

We start by analyzing the *random* controller, in which the motor commands were set randomly and independently so that there was no correlation among them. If we let the robot run long enough, in the limit we will encounter all possible combinations of motor commands of the four legs. The *random* controller can then be seen as marginalizing out the controller part of the controller-body-environment system. Hence, information structure obtained with this gait can be considered to be induced by the interaction between the body and the environment of the robot only. *Fig.* 5 shows the transfer entropy among all the variables in the *linoleum* ground condition. A cell of the matrix (a) indicates the information transfer from the signal in the column to the signal in the row.

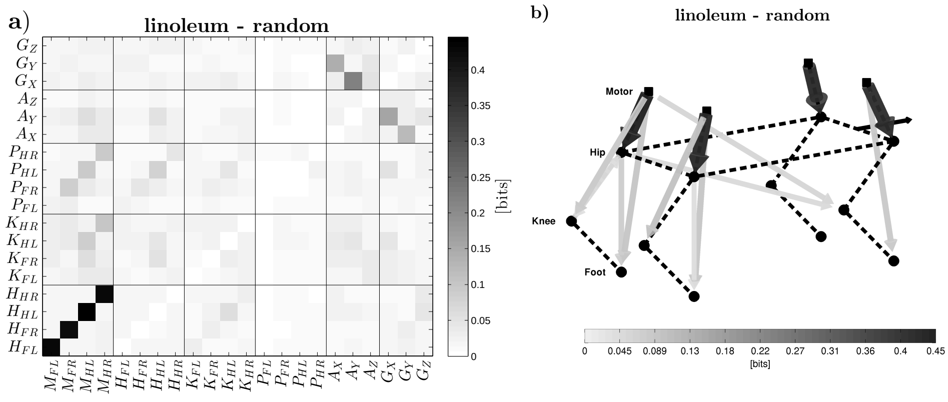

Fig. 5. **Transfer entropy TE in the *random* gait on *linoleum*.** **(a)** Every cell of the matrix corresponds to the information transfer from the signal on the column position to the signal on the row position. **(b)** A schematic of the Puppy robot (dashed lines) with overlaid arrows depicting the TE between the individual components. For readability, only the 15 highest values are shown and the accelerometers and gyroscopes were excluded from this visualization. The strength of the information transfer is encoded as thickness and color of the arrows.

The strongest information transfer occurs from the motor signals to their respective hip joint angles ($M_{FL} \rightarrow H_{FL}$, $M_{FR} \rightarrow H_{FR}$, $M_{HL} \rightarrow H_{HL}$, $M_{HR} \rightarrow H_{HR}$). The motors directly drive the respective hip joints and, despite some delay and noise, the hip joints always follow the motor commands, which induces a strong informational relation.

The motors further show a smaller influence on the knee angles (especially at the hind legs K_{HL} and K_{HR}) and on the feet pressure sensors, all on the respective leg where the motor is mounted. Finally, also the hip joints have some weak influence on the pressure sensors of the respective leg. The schematic of the Puppy robot in *Fig.* 5 (b) shows the same information flows as arrows with thickness and color depicting the strength of information transfer between the components (sensors from the IMU are not shown in this schematic). It can be seen that the information is mainly propagated within each leg, with stronger flows in the hind legs.

Other interesting relations revealed by the transfer entropy are between A_Y and G_X, and between A_X and G_Y. These reflect the robot's pitching and rolling movements, respectively, which are prominent motions in the quadruped robot.

When the robot rolls to one side, the gyroscope measures angular velocity around the X-axis (G_X), while the acceleration due to gravity partly projects into the Y-component, appearing in A_Y. Similarly the pitching movement affects the sensors A_X and G_Y.

Concluding, while the overall information in the gait induced by the *random* controller is quite low, the few relations that stick out reflect many things we know about the robot's physical structure and its behavior. In particular, the information flows between sensors and motors of the same leg are prominent, and the rolling and pitching movements induce flows between accelerometers and gyroscopes.

We propose that the contingencies derived from this gait constitute a rudimentary body representation of the robot. Of course this body schema is only valid in the environment the robot has experienced during the trials (*linoleum* in this case, but could be extended to all available ground conditions). We want to emphasize that contrary to the work in robotics dealing with self-recognition or self-calibration that we have reviewed in Sec. 1, the agent can arrive at this model with minimal assumptions or prior knowledge.

3.2.2. *Coordinated Motor Commands*

In the following, we will see how the information structure changes if we introduce controllers with coordinated, synchronized motor commands, which give rise to the *bound right* and *turn left* gait. The motor commands in these gaits are periodic oscillatory signals of the same frequency, but of different amplitudes, offsets and phase. Consequently, the robot exhibits periodic behavior and periodic-like signals are induced in the sensory channels.

From *Fig.* 6 (a, c) we see that the overall amount of information transfer is much higher than with the *random* controller. Furthermore, the information transfer no longer occurs only among the variables within one leg, but also among variables belonging to different legs. In the *bound right* gait (a, b), all motors (M) transfer much information to all hip joints (H). The knee joints receive as much information from the motors as the hip joints. In the *turn left* gait (c, d), on the other hand, the strongest influence of the motors is on the hind right hip (H_{HR}), followed by the hind knees. The pressure sensor P_{HR} receives more information than the other pressure sensors and the flows among different hip joints are very low except for the flows from the H_{HR} to the others. The special role of the hind right leg in the flows reflects the fact that the M_{HR} motor has a much higher amplitude and is a key contributor to the robot's locomotion (cf. video).

The information flows from the motors to the inertial sensors can be also related to the behavior displayed by the two gaits. The high flows from the motors to G_Y in the *bound right* gait relate to the pitching movement. The trajectories as observed by the overhead camera (*Fig.* 4 (a)) show a pronounced sidewards "zig-zag" movement during the *turn left* gait. This corresponds to the roll motion which is reflected in

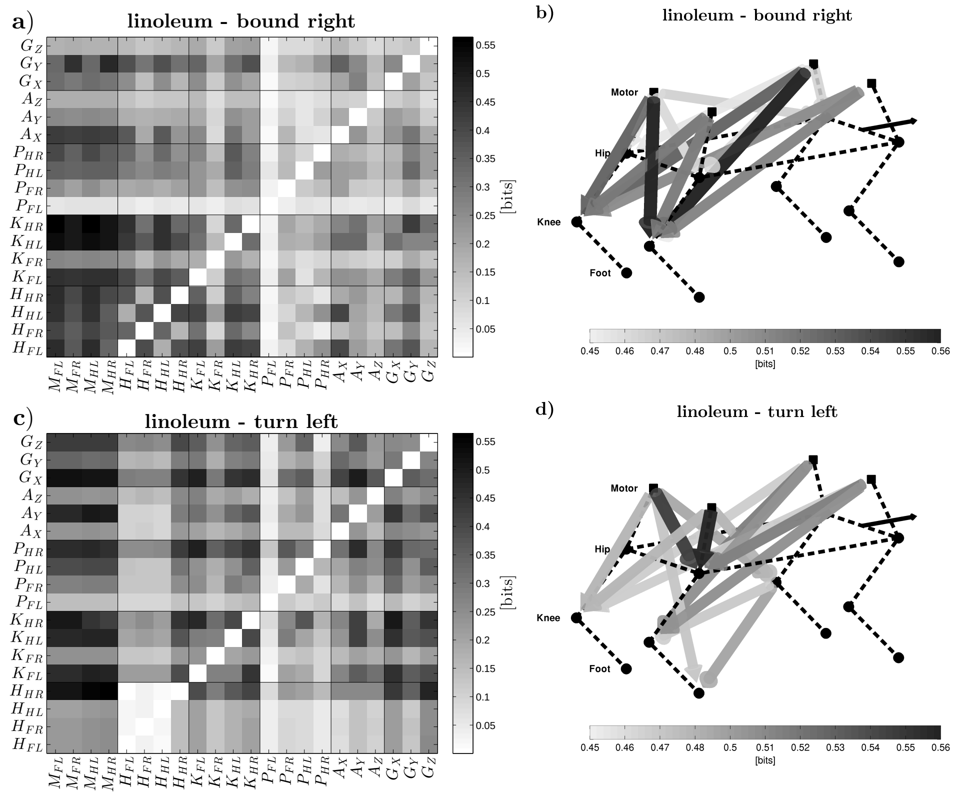

Fig. 6. **Transfer entropy in the coordinated gaits on *linoleum*.** The matrices and Puppy schematics show the transfer entropy in the *bound right* gait **(a,b)** and the *turn left* gait **(c,d)** in the same way as described in *Fig.* 5. Please note the different scale of the matrices and the Puppy schematics.

the high flows from the motors to A_Y and G_X.

All these examples show that the measured information flows strongly reflect aspects of the robot's behavior and the physical properties of its body. Furthermore, they show that periodic behavior induces specific informational structure through synchronization.

3.2.3. *Controllability*

Can maps of sensorimotor flow be utilized for control purposes, i.e. to achieve desired states or goals by the robot? As stated in Sec. 2.1, the transfer entropy from a controller to a variable expresses the controllability of this variable. Moreover, the decomposition into state-independent and state-dependent transfer entropy ($SITE$ and $SDTE$) allows to distinguish the open-loop and closed-loop controllability of the variable. This means the agent can infer the controllability of its sensory channels by its motors by looking at the flows from its actuators to its sensors. *Fig.* 7

shows this decomposed directed information transfer for the three sets of motor commands used in the Puppy robot. Part a) - from the random controller - hints on the controllability of the platform in general. We see that the hip joints can be controlled by the motors in the respective leg and there is indication that this can be done in an open-loop fashion, since the $SITE$ component is stronger [c]. The flows to the knee and pressure sensors, in particular in the hind legs, also hint on their possible controllability in an open-loop fashion.

Fig. 7 b) and c) depict the situation of the coordinated gaits. The information flows indicate higher open-loop controllability of the hips and the pressure sensors (stronger $SITE$ part). Although we saw in the previous section that in the coordinated gaits the knees receive more total information from the motors than the hips, the decomposition shows that this mainly comes from the $SDTE$ – their closed-loop controllability. So in order to control the knees, the feedback about their current state may be needed.

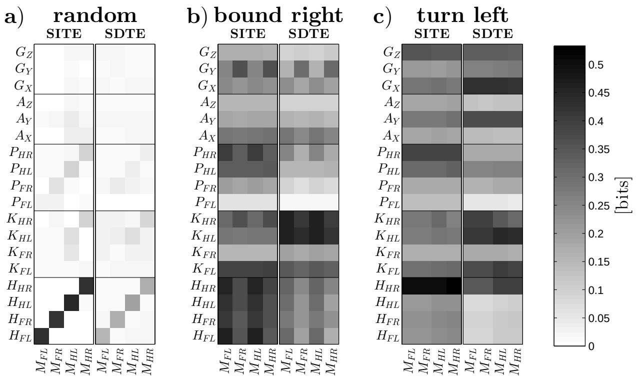

Fig. 7. **Decomposition of the transfer entropy.** The matrices show the decomposition of the information flows observed from the three controllers into $SITE$ and $SDTE$. Only the flows from the motors to the sensors of the robot are shown.

What would be the first goal-oriented behaviors that would be meaningful in the current situation? Let us imagine that the robot “wants” to accelerate forward or to turn. That is, a desired sensory state would be a high value of A_X or G_X respectively. From the information flows, we see that A_X is more affected by the motors in the *bound right* gait, whereas for G_X, it is the *turn left* gait that shows a stronger flow. The robot could thus choose a gait that would make the desired control action easier. Then, to obtain a simple controller, we would be interested in the “inverse” mapping - from the sensory variable to the motor signal - that would

[c]In reality, every hip is controlled with a closed-loop controller of the servomotor. However, this is hidden from the robot and hence, from a situated perspective, it is plausible to assume that they can be controlled in open-loop.

give us appropriate motor commands. This mapping could then be worked out as a functional relationships using regression, for example.

3.3. *Experiment 2: Influence of the Environment on the Information Structure*

In experiment 2 we let Puppy run with the *bound right* gait on five different grounds to investigate how the interaction with different environments changes the information structure.

3.3.1. *Ground Discrimination*

Fig. 8 shows the standard deviation of the information flows across the five ground conditions (after averaging the trials within the ground conditions). It reveals which flows are sensitive to changes of the ground and which remain constant. The matrix (a) shows that especially among motors and hip joints the relations are very strong and invariant to ground changes. On the contrary, the information that the hind left pressure sensor P_{HL} receives from many of the other channels, is very dependent on the ground condition, which can be seen from the arrows to P_{HL} in (b). We can again see that the flows reflect some properties of the robot's body: the hips follow the strong motors and are largely unperturbed by variations of the environment, while the pressure sensor measures directly the ground contact and can sense the differences (especially the hind left one, which takes the highest load during forward-rightward pushing in this gait).

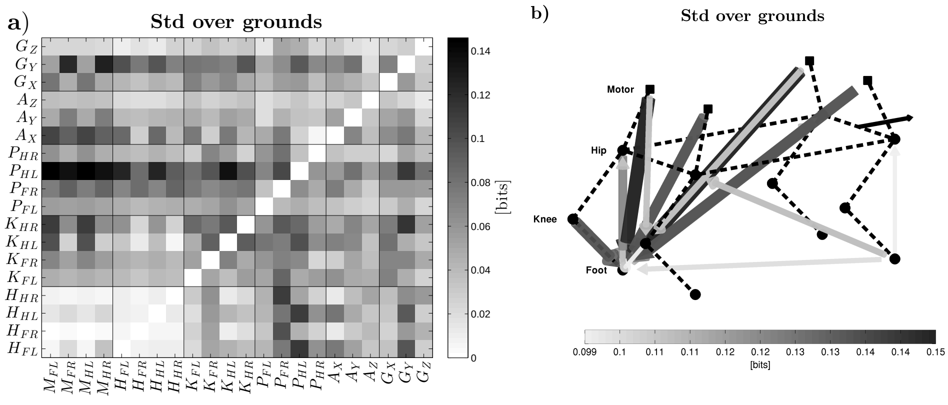

Fig. 8. **Information flow on different grounds.** The matrix **(a)** and Puppy schematic **(b)** show the standard deviation of the transfer entropy across the five ground conditions while running with the *bound right* controller. The standard deviation is calculated after averaging the trials within each condition.

We extended the analysis of variation induced by the ground conditions by a principle component analysis on the flows in all trials. The matrix in *Fig.* 9 (left) shows the resulting 1^{st} principle component of the transfer entropy. It shows that a lot of variation comes from the influence of the motor commands on the sensory channels. Especially the left knees (K_{FL}, K_{HL}), the pressure sensor P_{HL}, the accelerometer A_X and the gyroscope G_Y receive different information in different trials.

Plotting the information flow of all trials of the five ground conditions in the space spanned by the first two principle components (*Fig.* 9 (right)), confirms that the highest variance directions are indeed separating the ground conditions very well, and that trials on the same ground are clustered. This shows the robot's capability to distinguish the environmental conditions by observing the changes in certain information flows.

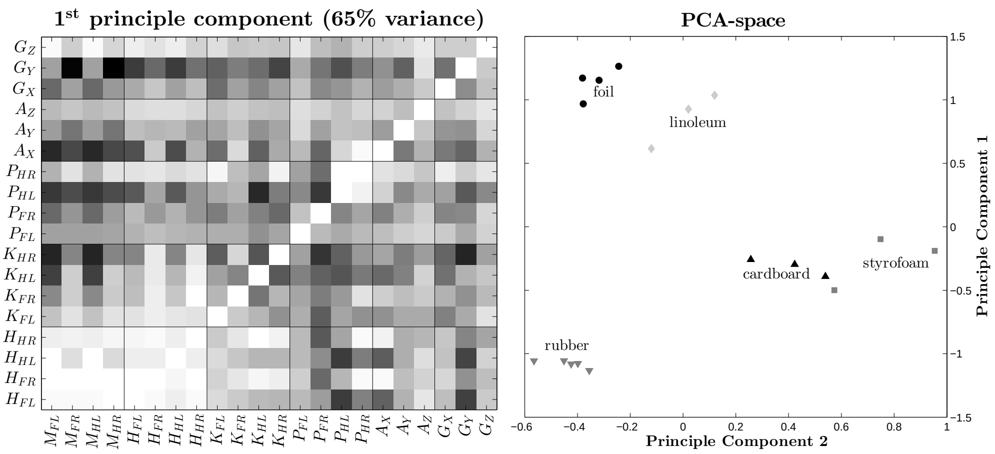

Fig. 9. **PCA of the information flows. (left)** The matrix shows the 1^{st} principle component of the information flows in all trials of the five grounds conditions while running with the *bound right* controller. **(right)** Information flow of all the trials projected onto the the first two principle components and labeled according to their ground condition.

3.3.2. *Stability and Friction*

Fig. 10 (b) shows the mean information transfer over all sensor and motor pairs depending on the friction coefficient estimate between each ground material and Puppy's feet. The amount of information transfer is negatively correlated with the friction coefficients ($r = -0.88$).

The dashed line in the figure shows a stability measure of the robot's locomotion. It measures the variation of all sensory channels from one period of locomotion to the next (perfectly periodic signals mean perfectly stable locomotion), and is highly correlated with the overall information transfer ($r = 0.995$). This also matches with an outside inspection of the robot's smoothness or comfort of locomotion, which is extremely smooth on the *foil* ground and becomes very difficult on higher-friction grounds, especially on *rubber* (cf. video). Therefore, the mean information transfer could serve as a possible reward or cost function that the robot could try to optimize - choosing the gait that has the highest score on a given terrain, for instance. Further explorations in this direction are necessary and could draw from existing work in this area [5, 27, 31, 36, 17].

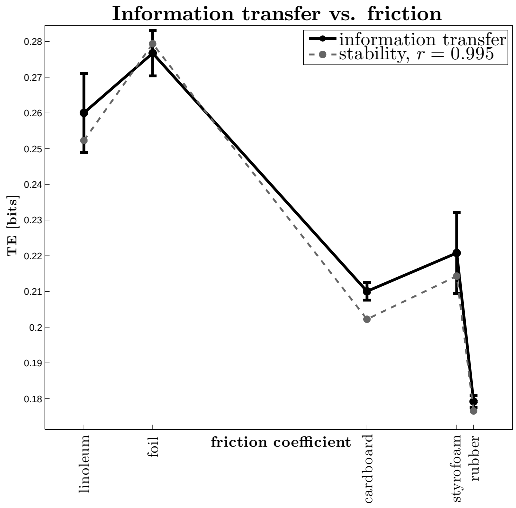

Fig. 10. **Information transfer vs. friction.** The mean information flow across all variable pairs is plotted against the static friction coefficient estimate in each ground condition (black solid line with error bars). In addition, the stability (dashed gray line) is depicted. The stability is calculated from the standard deviation of all sensor signals across locomotion periods (a perfectly stable behavior would be perfectly periodic and have zero variation, whereas an unstable behavior would show some variation and thus have a negative value in this stability measure).

3.4. *Sensorimotor Contingencies*

3.4.1. *Proprioceptive and Exteroceptive Sensors*

Sensors that an agent possesses are often classified into proprioceptive and exteroceptive. For robots, Siegwart et al. [35] define *proprioceptive sensors* as those that measure values internal to the robot (e.g. battery voltage, joint angle sensors) and *exteroceptive sensors* as those those that acquire information from the robot's environment (e.g. distance sensors, cameras). However, these classifications rely on an *a priori* knowledge about what is internal to the agent and what is external environment. We will assume that this is not known to our robot, the agent is only confronted with the signals reaching its "brain".

Philipona et al. [30] define the agent's body as part of the world over which it has complete control. Consequently, proprioceptors are defined as input channels with high controllability. We adopt the notion of controllability from [42] as being quantified by the information transfer from a controller (motor commands in our case) to a variable (sensors in our case). In this sense, "proprioceptiveness" is not an all-or-nothing classification of a sensor, but rather a continuous property. *Fig.* 11 (left) visualizes this for Puppy's sensors. It shows the information flow from the four motors (M_{FL}, M_{FR}, M_{HL}, and M_{HR}) to each sensory channel. We can immediately spot that the hip angular sensors stand out. They receive very high information flows from the respective motor signal of the same leg. Thus, the agent could attribute the proprioceptive property to the hip potentiometers. While the other sensors do not reach as high values, some degree of "proprioceptivness" can still be observed. We can see that the knee and pressure sensors also receive significant information flows from their respective motor signals on the same leg.

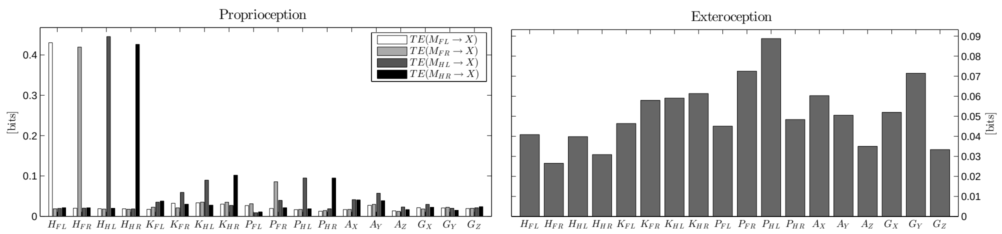

Fig. 11. **Proprioceptive and exteroceptive sensors. (left)** Proprioception is defined as the information flows from motor signals to each sensory channel under the *random* gait on the *linoleum* ground. The four bars in each sensory channel represent the flows from the M_{FL}, M_{FR}, M_{HL}, and M_{HR} motor signal respectively. **(right)** Exteroception is defined as an aggregate measure of how the information flows to and from each sensor vary when the ground is varied (standard deviation across five grounds with the *bound right* gait).

Exteroceptors can be defined as the channels that are sensitive to changes in the environment. In Sec. 3.3 and *Fig.* 8 we have shown that the information flow between each motor-sensor or sensor-sensor pair varies when the ground changes. By averaging over this standard deviation of all incoming and outgoing flows of a channel (row and column involving this channel), we can estimate the overall level of proprioception of each channel individually. *Fig.* 11 (right) shows the "exteroceptiveness" for each channel and it shows that this is again not an all-or-nothing property, but a graded distinction of the channels.

Compared to classical sensor classification, where angular and inertial sensors are classified as proprioceptors and tactile (pressure) sensors as exteroceptors, our interpretation derived from the information structure provides a very different picture, as can be inspected in *Fig.* 12 (left), where the two sensor characteristics are plotted against each other. Whereas the hip angular sensors are clearly identified as proprioceptors, their "colleagues" in the knee joints show both properties to a similar extent. In the context of our robot, we find this plausible. While the hips are directly driven by motors, the knee joints are passive and are also highly dependent on the interaction with the ground. Similarly, the inertial sensors seem to be more responsive to environmental changes than to the individual motor signals.

We want to argue that the sensor classification as we have just demonstrated reflects much more the reality as experienced by the agent than the classical textbook classification would.

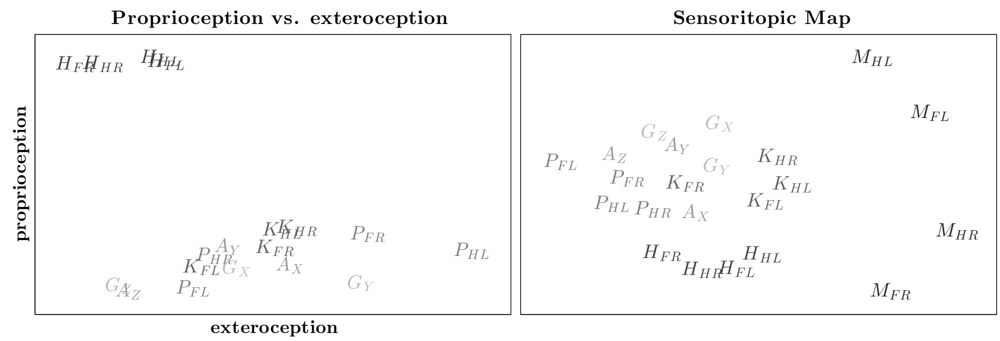

Fig. 12. **Sensor spaces. (left)** Proprioception vs. exteroception. The values from *Fig.* 11 are plotted against each other. **(right)** A Sensoritopic map. Projection of the sensors and motors into 2D space using multidimensional scaling based on a information flow-based similarity measure.

3.4.2. *Learning about Sensory Modalities*

According to O'Regan and Noe [26], it is the "structure of the rules governing the sensory changes produced by various motor actions" what differentiates modalities. The directed information flows that we have quantified provide the basis for such a structure. The agent could assign two channels that are similar to a common modality. Similar in terms of information flows means that they send and receive same amounts of information to/from the same channels[d]. In *Fig.* 12 (right) we show how such an information flow-based similarity measure leads to a map of the agent's sensor space, a sensoritopic map, by projecting the channels onto a 2D plane where their distance reflects their similarity[e]. The resulting map shows a reasonable clustering of channels belonging to same modalities. In particular, the motors are located on the far right, the hip joint angles come together at the bottom, the knee joint angles central and the pressure sensors on the left. The inertial sensors are scattered between the knees and pressure sensors towards the top. The lack of topological relationships (sensors of the same leg do not come together) comes probably from the fact that in our platform, there are few separated physical

[d]This distance metric used here is the Euclidean distance between the rows and columns of two sensors in the information transfer matrices.
[e]This was achieved by multidimensional scaling, similar to what has been done in [25].

relationships. As the robot runs, through the interaction with the environment, the influence of one leg gets propagated to all the other legs.

3.4.3. *Predictive Capacity*

Transfer entropy measures how knowing the state of one channel helps in predicting the state-transition of another channel. Thus averaging all the values in a column of a transfer entropy matrix will give us an aggregate "predictive capacity" of each channel. The predictive capacity can serve as an indicator of the channel's quality or utility for the agent. The result of this analysis is depicted in *Fig.* 13. Not surprisingly, the motor signals have the highest score. They are controlling the system and should thus be most effective in predicting the sensors' future states. Among the sensory channels, some hip and knee angle sensors have high values. These are good candidates to focus attention on. Conversely, sensors with low scores (e.g. P_{FL}) could receive less attention or be marked for replacement.

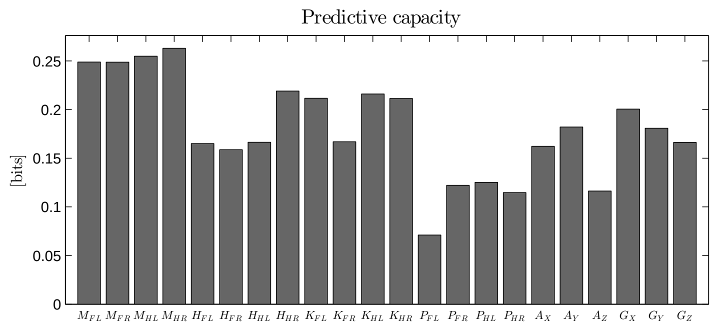

Fig. 13. **Predictive capacity.** The mean information transfer from each sensor or motor to all other channels (mean across all gaits and the ground conditions *foil*, *linoleum* and *styrofoam*).

4. Discussion

The measure we used to analyze the information flows in time series was transfer entropy. In addition, in the analysis of the information transfer from the motors to the sensors, we have employed its decomposition into state-independent (SITE) and state-dependent transfer entropy (SDTE), motivated by its relationship to open-loop and closed-loop controllability [42]. Transfer entropy fulfilled our criteria as a method capable of extracting directed nonlinear relationhips. Other information theoretic methods could possibly be applied, however, a quantitative comparison of different methods was not the purpose of the current study (see [9] for a study along these lines). Nevertheless, all methods that rely on observing time series only have difficulties separating real causal effects from spurious correlations. There, interventional methods [28, 1] could be used to refine the relationships that we have extracted.

We have used a real, dynamic, nonlinear platform equipped with 18 sensors encompassing multiple sensory modalities. We want do discuss a number of points regarding this choice. First, in our view, this platform bears a fair level of ecological validity and would satisfy what Ziemke [44] has called “organismoid embodiment”: an organism-like bodily form with sensorimotor capacities akin to living bodies (though our dimensionality is still much lower compared to sensorimotor spaces in biology). This contrasts with the studies on artificial agents in which highly simplified abstract worlds are often used. Second, the nature of legged locomotion - a periodic behavior composed of alternating phases of leg touchdown and lift-off - poses specific challenges. Special care needs to be taken when applying information transfer analysis to periodic signals. The contacts with the ground, on the other hand, introduce sharp discontinuities in the dynamics. This contrasts with robotic case studies, where the environment is sampled by a smoothly moving camera. Third, distal or “visual” sensors are completely absent in our case. Hence, our robot cannot see itself and thus can obtain almost no information about its state while being static. Active generation of information is thus indispensable and the sensorimotor flows that we analyze uncover complex implicit dynamic relationships in a running legged robot, rather than straightforward geometrical transformations.

Let us look at our case study from an engineering perspective as well. The relationship between motor and sensory signals that we have analyzed would fit into the scope of system identification methods (e.g. [18]), possibly giving rise to a model of our robot (the plant). This could be of a grey-box, where knowledge about the system would enter the model, or black-box kind - corresponding to our situation, where the agent has little prior knowledge regarding its body, environment and nature of actuators and sensors. In fact, the input signals that we have used in our scenario - periodic and random motor signals - correspond to possible ways of exciting a system in open loop from system identification [18, 12]. The random motor signal has the advantage of being “rich” enough - containing many frequencies. In addition, it does not contain any information structure in it, which proved very useful in our situation - we have found that the information theoretic analysis is very sensitive to structure from a periodic motor signal being “imposed” on the sensory signals. Can our study inform the system identification community? We propose that an information-theoretic analysis of the kind we have performed could act as a first step that would reduce the dimensionality of the problem and point to the important relationships which can be later modeled in detail (using transfer functions, for instance).

5. Conclusion and Future Work

In this paper, we have analyzed the sensorimotor flows in a running quadruped robot using transfer entropy and studied the impact of different environmental conditions as well as motor signals on the information flows. Then, we have adopted a situated perspective (looking at the world through the "eyes", i.e. sensors, of the autonomous agent) and proposed a number of ways in which the agent could use the tools of information theory to discover the regularities in the sensorimotor space that its interaction with the environment induces and use these to bootstrap its perception and cognition.

We see a lot of potential for future work in both the analytical and the application part of our case study. In the analysis, first, we have looked at information flows between pairs of variables (motor or sensor) only. The method could be extended to multivariate information transfer as suggested in [42]. Second, in the analysis of pairs of time series, we have collapsed the time dimension by selecting the time lag at which the information transfer was maximum. However, the exact timing of the information transfer is important for control purposes as well as for perception and cognition, as demostrated by Williams and Beer [42] in a simple evolved agent. Third, we have applied only simple tools to analyze and visualize the sensorimotor structure. However, graph theory would offer further machinery that would be relevant. One could generate subgraphs based on connected components - these would correspond to local relationships, such as the motors and sensors in one leg of the robot.

We have outlined a number of directions in which understanding the structure of the sensorimotor space could bring behavioral advantage to the robot. We feel that it will be fruitful to elaborate these scenarios more concretely and put them to test. First, we have touched on the controllability in Sec. 3.2.3, where we have identified motors that could be used to control some target sensory variables. In order to acquire a controller, the knowledge that a control relationship exists, needs to be converted to a functional relationship. Edgington et al. [6] propose a method in this direction based on turning joint probability distributions into regression functions. In this way, a simple open-loop controller could be directly obtained. Second, we have shown how different environments induce changes in the flows in the sensorimotor space. In a different study on the same platform [15], we have employed sensory features to discriminate different grounds. In the future, it would be interesting to compare these results with features that use information flows instead (we show first results in Sec. 3.3.1). These features may prove to be more robust as they better reflect the overall dynamics of the robot interacting with the ground. Third, we propose that the agent can exploit the knowledge about the structure of the sensorimotor space to economically allocate its computational resources. The predictive capacity measure we have introduced in Section 3.4.3 is a rough approximation of a sensor's utility or quality that can provide a useful bias to guide the agent's attention. Furthermore, having such a measure of sensor quality can be exploited further if the agent has the possibility to change the morphology of its sensors online. If the physical placement of the sensor can be adjusted, then the agent can optimize these in order to get the most information out of each sensor. If sensor values are being discretized, then the resolution can be adapted - "good" sensors can be sampled with more bins, for instance. Finally, if the robot detects very low information flows in one of the channels, such as the front left foot pressure sensor (P_{FL} in *Fig.* 13) in our case, this may indicate a failure. Depending on its capabilities, the robot could either try to repair the sensor or it could signal its failure.

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Appendix E

Dead reckoning in a dynamic quadruped robot: inertial navigation system aided by a legged odometer

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Note: The contribution of both authors to this work was equal.

Dead reckoning in a dynamic quadruped robot: inertial navigation system aided by a legged odometer

Michal Reinstein and Matej Hoffmann

Abstract—**It is an important ability for any mobile robot to be able to estimate its posture and to gauge the distance it travelled. The information can be obtained from various sources. In this work, we have addressed this problem in a dynamic quadruped robot. We have designed and implemented a navigation algorithm for full body state (position, velocity, and attitude) estimation that does not use any external reference (such as GPS, or visual landmarks). Extended Kalman Filter was used to provide error estimation and data fusion from two independent sources of information: Inertial Navigation System mechanization algorithm processing raw inertial data, and legged odometry, which provided velocity aiding. We present a novel data-driven architecture for legged odometry that relies on a combination of joint sensor signals and pressure sensors. Our navigation system ensures precise tracking of a running robot's posture (roll and pitch), and satisfactory tracking of its position over medium time intervals. We have shown our method to work for two different dynamic turning gaits and on two terrains with significantly different friction. We have also successfully demonstrated how our method generalizes to different velocities.**

I. Introduction

It is a strong requirement for any mobile agent, animal or robot, to be able to estimate its posture and to gauge the distance it travelled. The former is usually crucial for successful locomotion; the latter for navigation. The information can be obtained from various sources, which include visual information (optic flow, landmark detection), inertial sensing, other self-motion cues (proprioceptive information from joint sensors on legs for instance), or compass measurements. Furthermore, robots have recently acquired an additional powerful source that is not available to their biological counterparts: absolute position information from a Global Positioning System (GPS). All the above-mentioned sources of information have their pros and cons, regarding their precision, sampling rates, reliability, or cost. Generally, superior performance compared to the use of a single modality can be obtained through sensor fusion.

In robotics, wheeled vehicles are the most common platforms on land. There, a popular solution is an inertial navigation system (INS) aided by a GPS (e.g., [1]). Other sources of aiding are also used (e.g., vision [2], ultrasonic [3]). Aiding by external reference is indispensable if long-term position precision is to be guaranteed, but all aiding systems have limitations.[1] In this paper, we are interested in fully autonomous navigation - a system that does not rely on any external reference, i.e. it is based purely on self-motion cues. This problem is known as dead reckoning.

We have decided to use an inertial measurement unit (IMU) as our primary sensor. However, since neither the absolute position nor heading can be sensed directly, double integration of the inertial sensors signals inevitably results in a drift in estimates due to sensor noise. What other information (rather than external reference) can be used for aiding? First, an odometer measuring the rotations of wheels is a frequent solution. Second, a kinematic model of the vehicle can be used, typically to provide velocity constraints that can be used for aiding. Both aiding sources were fused with an inertial navigation system (INS) in [4][5].

Compared to wheeled applications, there is much less work addressing legged platforms. This problem is much harder. First, it has more dimensions: unlike a wheeled vehicle, a legged platform's motion involves pitching and rolling motions, as well as vertical motion that includes even aerial phases. Second, its way of locomotion is much more complex and harder to model. Third, it is far from clear how an odometer could be implemented.

In legged robots, the attitude estimation problem alone was addressed in walking humanoid robots (e.g., [6]) and quadruped robots [7]. On the other hand, position estimation only, with GPS aiding in a quadruped was addressed in [8].

The contribution of M. Reinstein and M. Hoffmann to this work was equal.

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[1] For instance, signal robustness, availability, and accuracy issues can be listed among the drawbacks of a GPS; visual landmarks pose availability and recognition issues; interference often disrupts magnetometer aiding.

However, to our knowledge, the full body pose problem without external reference aiding in a legged robot has been addressed by Pei-Chun Lin et al. only; they have used the hexapod robot RHex. In [9][10] a strain-based leg sensor is used to estimate the kinematic configuration of the legs of the robot. From the configuration of the legs, the pose of the whole robot was estimated. Under some assumptions (tripod gait, the body is supported by at least three legs with non-collinear toes at any given time, ground contact legs have no toe slippage), position increments were obtained. Some of the assumptions are alleviated in [11], where fusion with inertial sensors ensures full body state estimation in a jogging gait. However, the model is still complex, involving four phases: tripod stance, liftoff transient, aerial, and touchdown transient phases. Different speeds and grounds were addressed; the architecture proved not to be immune to slippage though.

Our work extends the above-mentioned concept in a number of aspects. First, we have decided to aid velocity rather than attitude. Our inspiration came from the animal kingdom, especially the work on mammals and arthropods (e.g. [12][13][14]), which does not exclude the possibility that velocity and distance may be gauged from locomotor self-motion cues only. Velocity can be obtained as a product of frequency of locomotion (given by the motor signal) and stride length (which can be obtained from sensors on legs). In this work, we have devised such a legged odometer. Second, our model is data-driven, or empirical, rather than analytical. Third, the odometer is based on a fusion of multiple sensors – hip and knee angular sensors, and feet pressure sensors. Fourth, the proposed architecture can not only deal with different velocities, but also with substantial slippage. Fifth, we have tested the proposed system on different gaits, including their transitions. Finally, the gaits employed were not straight, but turning; our navigation system was thus naturally tested in an additional dimension.

The paper is structured as follows. First, we will present the introduction into the theory regarding inertial navigation systems, Kalman filtering, and explain our data fusion scheme. Second, we will briefly describe the experimental setup. Third, we will explain the method we devised to develop a legged odometer. Fourth, we will demonstrate the performance of our navigation system in a series of experiments. Finally, we will conclude by discussing the implications of the results and possible future work.

II. Theory and Methodology

A. Inertial Navigation Systems

A conventional IMU is composed of three accelerometers and three angular rate sensors, mounted perpendicularly to each other to create an orthogonal measurement frame [15 p. 12]. Therefore, each accelerometer is able to detect the specific force that is defined as the time rate of change of velocity relative to local gravitational field [16], [17]. For navigation in any frame, it is important to track directions in which the accelerometers sensing axes are oriented by sensing the rotational motion using angular rate sensors [16], [17]. Compensation for projected local gravity value, Coriolis and centripetal acceleration has to be resolved too.

B. INS Mechanization Algorithm

By definition, strapdown mechanization is an algorithm that converts raw inertial data into navigation variables, i.e. velocity, position, and attitude [15 pp. 29-39]. We have developed a strapdown mechanization by combining the approaches described in [16], [17], [18 pp. 61-75], with enhancements proposed in [19]. Our implementation of the strapdown mechanization determines the navigation variables from raw inertial measurements by integrating differential equations describing the motion dynamics that can be found in [19 p. 29]. The strapdown mechanization algorithm proceeds with the following steps: compensation of sensor errors, numerical integration of the sensor outputs, velocity update, position update and attitude update. In our implementation, we have employed a quaternion approach exploiting the multiplication chain rule and the Bortz equation for computation of rotation vectors. The experimental evaluation of our strapdown mechanization can be found in [20], [21].

C. Extended Kalman Filter (EKF)

The Kalman Filter (KF) [22] has been widely used in INS state estimation and filtering. It combines all available measurements with prior knowledge about the sensing device and the system to produce an optimal state estimation that statistically minimizes error. Since the exact model of the system and measurements are not available in real life, and the statistical characteristics of the process and measurement noise are difficult to determine, the major task is to choose an appropriate model.

In navigation applications the KF appears in many variations such as the extended Kalman filter (EKF), which deal with non-linearities of the system model equations (see e.g., [19], [23]). For a long time, EKF has been playing a key role in navigation software design. Whereas the KF estimates states of a linear system model only, the EKF can estimate states of a nonlinear system model, but only up to a certain level of nonlinearity [24 pp. 176-182]. The choice of an appropriate model is a crucial issue since only small state values are allowed to be delivered to the EKF. Because of the first order approximations, large values can cause biased solutions and inconsistency of the covariance update [19]. Therefore, instead of using state vector representation of absolute values, we implemented the EKF to estimate only small errors given by an error model. Detailed description and derivation of the EKF equations that we implemented can be found in [24 pp. 179-180].

D. Error Model for Data Fusion

To develop an error model for data fusion, we considered the theory regarding sensor error propagation as in [24 pp. 172-178]. Our error model is based on the classical 15-state concept thoroughly described in [25 pp. 35-41], [26 p. 20]. We have taken the uncoupled approach to the classical perturbation analysis as proposed in [25] to obtain equations capturing the error dynamics from the differential equations describing the motion dynamics. These perturbation equations were linearized and errors of the second order and higher were neglected. Then the equations were expressed in terms of position, velocity, attitude errors, and sensor errors to form the desired linearized error model. This model with the appropriate proof can be found in [25 pp. 35-41].

E. Data Fusion Scheme

In general, data fusion schemes can be classified according to the architecture of the system and the data fusion method employed [23 p. 70]. Due to the nature of the EKF, we constructed the data fusion scheme as a centralized processing approach combined with closed loop state estimation. The architecture therefore corresponds to a conventional complementary filter, where two independent sources of information are combined in the sense that they compensate for each other's limitations [27]. The whole data fusion scheme is shown in Fig 1.

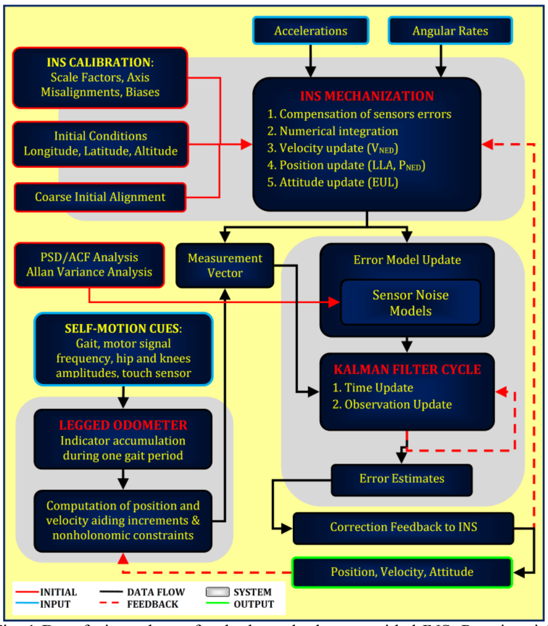

Fig. 1 Data fusion scheme for the legged odometer aided INS. Raw inertial data, three accelerations, and three angular rates enter the system at a rate of 100 Hz. The navigation algorithm is initialized with the calibration parameters for inertial sensors and initial position information for computing local gravity value; coarse alignment proceeds to estimate the initial heading. **INS mechanization block**: The output of the INS mechanization algorithm is the updated velocity vector, position vector and attitude vector. **Legged odometer block**: In parallel with the INS mechanization, the legged odometer proceeds to process the self-motion cues data measured at 50 Hz, asynchronously according to the gait period. The gait and its frequency are monitored and according to the predefined indicators, the stride length is computed for each gait period. The output of the legged odometer over one gait period is converted into the aiding signal to form a measurement vector that enters the EKF. The aiding signal is stored in a buffer and upsampled ten times to provide higher aiding rate. **Error model update block**: The output of the INS mechanization algorithm together with the parameters of the inertial sensors noise models determined using Allan variance analysis [28] are used at each time step to update the error model (for details regarding sensor noise modeling see previous work [29]). **Extended Kalman filter cycle**: If the measurement vector is not provided, i.e. the aiding is unavailable, the EKF runs only as a predictor with the Kalman gain set to zero. If at least one EKF update has occurred and if sufficient time has passed to build up the errors, feedback to the INS mechanization algorithm is provided and correction of errors proceeds. Each time this feedback occurs and the errors are corrected the state vector is reset to zero to prevent unbounded error growth.

III. EXPERIMENTAL SETUP

A. Robotic Platform

The robot used has four identical legs driven by position-controlled servomotors in the hips. In addition, there are four passive compliant joints at the "knees". A photograph and schematic can be seen in Fig. 2. The mechanical design (weight distribution, proportions, springs used etc.) is a result of previous research (e.g., [30]). In addition, a new material was added onto the robot's feet which has asymmetrical friction properties, allowing the robot to get a good grip during leg retraction (stance), but enabling some sliding during protraction (swing).

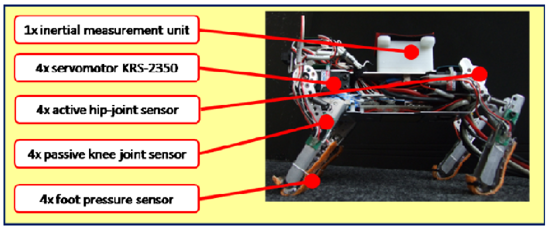

Fig. 2 Quadruped robot (Puppy II) with MTi-OEM (Xsens) inertial unit.

We applied a simple oscillatory position control of the motors. The target joint angle of each motor γ_i^* (and hence of each leg) was determined as:

$$\gamma_i^*(t) = A_i * \sin(2\pi * f * t + \theta_i) + B_i,$$

where the oscillation can be varied by changing the amplitude A_i, offset B_i, frequency f, and phase θ_i parameters. The target angles are then sent to the local PID controller of the servomotors. Different parameter settings resulted in different gaits. We applied two turning gaits that resulted from experimentation: a highly dynamic right-turning gait derived from a bounding gait, and a less dynamic left-turning gait, where higher amplitude of the hind right leg was responsible for the resulting turning behavior (see accompanying video). The sensor suite used is displayed in Fig. 2. Non-inertial data were provided at 50 Hz, inertial data at 100 Hz. The inertial measuring unit (MTi-OEM, Xsens) was recording raw but calibrated sets of inertial data (angular rates ±300 deg/s, accelerations in ±50 m/s^2 range).

B. Arena

During the experiments the robot was running in an arena of roughly 2.5 x 2.5 m and was tethered.[2] An overhead camera attached to the ceiling was used to observe the robot. Later, the position of a red-colored marker placed roughly above the robot's Center Of Mass (COM) was tracked. A

[2] Cables were used to provide power, as well as for communication with the robot. Although they did affect the robot's dynamics, effort has been made to minimize these effects.

screenshot from the video tracking software (Tracker) showing also the arena can be seen in Fig. 3.

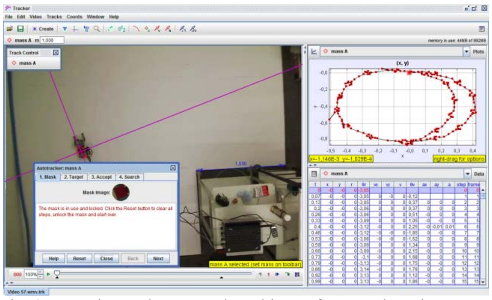

Fig. 3. Experimental setup and tracking software. The robot was running in an arena (here on Styrofoam surface) and was tracked from a single camera attached to the ceiling. Afterwards, a tracking software was used to obtain the trajectory of the robot's center (red marker).

IV. Legged Odometer Development

Mathematical kinematic models of legged robots can provide velocity estimates. This is fairly straightforward for statically stable robots with stiff, position-controlled limbs. The advancement of the COM can be obtained through a rigid body transformation from the leg joint positions [8] [31]. If the model is correct, this approach guarantees good results as long as there is no slippage of the feet. However, in reality, this is rarely the case and contact modeling itself is a notorious issue in the modeling of legged systems that is often responsible for a "reality gap". Dynamic locomotion poses even more difficulties. If an aerial phase is involved, the model has to be split into several phases [11].

In our particular case, additional factors make such explicit modeling inappropriate. The robot is underactuated with passive compliant knee joints, whose trajectory thus cannot be commanded (though it can be measured). There is no active ground clearance and slipping feet in both directions are an integral part of the gaits the robot uses. In addition, the feet are covered with a material that has different friction in forward and backward direction for better locomotion capability.

Therefore, rather than modeling the robot's motion, we decided to exploit the sensors on the robot to obtain a distance travelled / velocity estimate. However, unlike in wheeled odometry, this information cannot be obtained in any direct manner. Given the periodic nature of legged locomotion, velocity can be obtained as

$$v = frequency * stride\ length.$$

Whereas frequency can readily be obtained from the control parameters that drive the robot, *stride length*[3] is our variable of interest. What indication could the joint position sensors in active hip/shoulder joints and passive knee joints, and pressure sensors on the robot's feet give? We have adopted a data-driven approach and addressed multiple velocities, gaits, and terrains. This section illustrates the proposed methodology for 1 gait (right turning bounding) and 1 type of ground (Styrofoam). The method can be divided into the following phases:

A. Measurement Phase

Several motor frequencies were used and the robot's motion was tracked using an overhead camera. Afterwards the data was searched for correlations among stride length and indicators derived from the sensory data.

Fig. 4 presents the recorded trajectories of the quadruped robot when running with the right-turning bounding gait under different frequencies. These constituted the training set. Fig. 5 shows the evolution of the stride length.

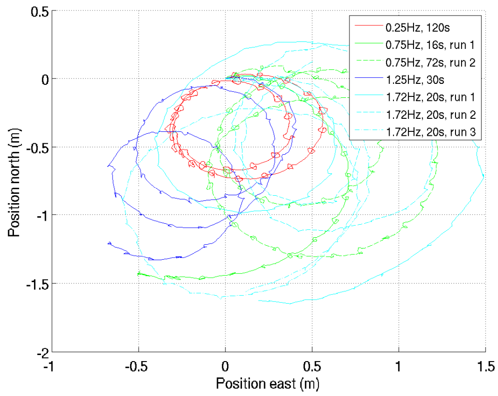

Fig. 4. Trajectories resulting from tracking of quadruped robot with the right-turning bounding gait under different frequencies.

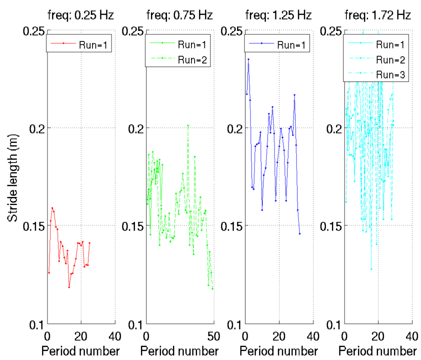

Fig. 5. Stride length measurements in individual periods of locomotion.

Together with tracking the position, all sensory-motor data from the robot was recorded. These were the angular position signals from the actuated hip joints, from the passive knee joints (Fig. 6, top), and from feet pressure sensors.

We were interested in the relationship between the sensory data and stride length. Since stride length is distance travelled in one period of locomotion, we decided to compress the sensory data to indicators that carry information about the whole locomotion period. For the angular position sensors, we decided to use the amplitude (obtained from absolute value of a Hilbert transform of the sensory signal) of every period (Fig. 6, bottom); with the

[3] The distance from initial contact of one foot to the following initial contact of the same foot. Sometimes referred to as cycle length. Essentially, this is equal to the distance travelled in one period of locomotion.

feet pressure sensors, we decided to integrate the pressure values during the period.

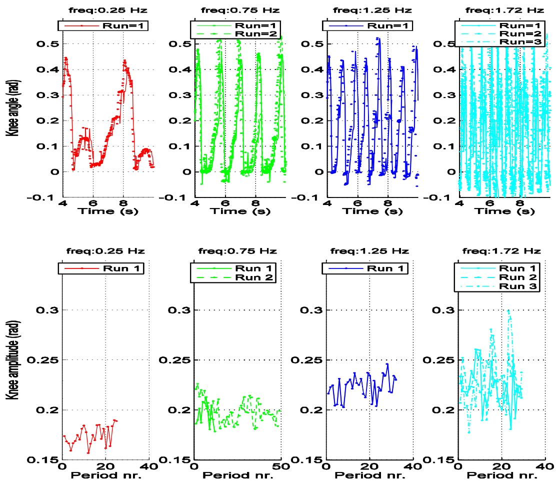

Fig. 6. Knee joint angles and amplitudes at different frequencies – fore right leg. (Top) Knee joint angle data from six seconds of movement. (Bottom) Knee joint amplitudes, period by period.

B. Correlation Investigation Phase

Once the data was collected and preprocessed, we investigated the relationship between the period-based indicators coming from the sensory and motor data (frequency of the gait was also included), and stride length. Using our intuition and experimentation, we came up with a set of compound stride length indicators. These were composed of sums or ratios of the individual period-based indicators. We explored linear relationships only, with the help of a Hinton diagram (Fig. 7). The most significant correlations with stride length (first row or column) were extracted. Fig. 8 shows the raw data underlying these correlations. There is a positive correlation between stride length and frequency, and negative ones between stride-length and left-to-right knee amplitude ratio, sum of hip amplitudes, and sum of pressure sensor integrals of all legs.

C. Indicator Fitting and Combination

We have shown that there are relationships between stride length and the sensory and motor data. However, since our final goal was to obtain an estimate of stride length from the data, we needed to express the dependent variable, stride length, in terms of the independent variables, the indicators. In a natural extension of our method, which was looking for linear relationships, we have fitted the stride length vs. indicator data with lines in a least square sense. Root mean square fitting error was an indicator of the quality of the fits. The indicator set that was used in the current situation (right-turning bounding gait) was:

$$SL_{freq} = 0.04 * frequency + 0.13$$
$$SL_{L2R\ knee\ amp} = -0.08 * leftToRight\ knee\ amp + 0.29$$
$$SL_{sum\ hip\ amp} = -0.38 * sum\ hip\ amp + 0.98$$
$$SL_{sum\ feet\ pressure} = -0.000019 * sum\ feet\ pressure + 0.25$$
$$SL_{sum\ knee\ amp} = 0.20 * sum\ knee\ amp - 0.12$$

Finally, we have decided to recombine the indicators to obtain one robust estimate. This was done by recombining the individual indicators with weights inversely proportional to their fitting RMS error on the training set. In our current case:

$$SL_{combined\ estimate} = 0.21 * SL_{freq} + 0.21 * SL_{L2R\ knee\ amp} + 0.20 * SL_{sum\ hip\ amp} + 0.19 * SL_{sum\ feet\ pressure} + 0.19 * SL_{sum\ knee\ amp}$$

The prediction error of the individual indicators as well as the combined indicator was between 10% and 15% of the stride length value.

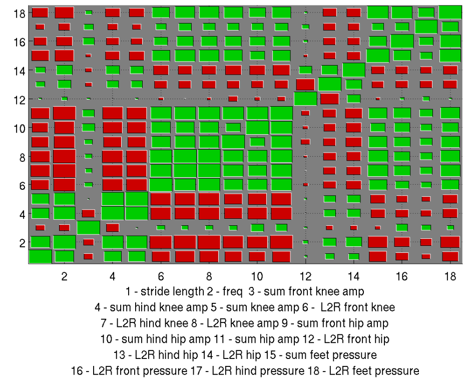

Fig. 7. Hinton diagram showing the correlations between different period-based indicators. Green color stands for positive, red for negative correlations. The size of each rectangle is directly proportional to the absolute value of the correlation. The first row depicts correlations with stride length.

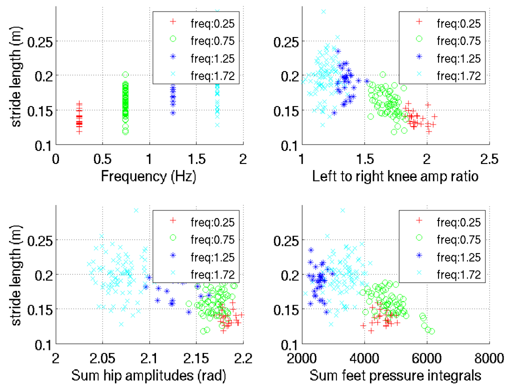

Fig. 8. Relationship between stride length and sensory or motor indicators at different frequencies.

However, we were more interested in how this estimate generalizes to previously unseen runs, and more importantly to unseen frequencies (and hence velocities). We also wanted to see if the method can cope with different terrains and gaits. We report these results together with the resulting fusion with inertial sensors in the next section.

V. Experiments and Results

We have conducted several experiments to illustrate the performance of the proposed navigation system – inertial navigation aided by a legged odometer using the EKF for data fusion and error estimation.

A. *Experiment 1 – Generalizing to Unknown Velocity*

In the first experiment, the robot was running for 20 seconds with the right-turning bounding gait at 1 Hz. This frequency was not in the training set.

1) Position Estimation: Fig. 9 (top) shows the performance of estimating the translational state of the robot (blue line). The performance of the dead reckoning system is satisfactory, with an average RMSE in position of 0.06 m (with robot's body length of 0.2 m).[4] Fig. 9 (middle) presents the performance of stride length aiding (legged odometer) and final estimation (after fusion with inertia) in consecutive movement periods. Since the frequency for the gait used in this experiment was not in the training set (0.75 and 1.25 Hz were the neighboring frequencies that were included), we have hinted on the generalization capabilities of the legged odometer.

2) Attitude Estimation: The evolution of attitude angle estimates is presented in Fig. 9 (bottom). The periodic dynamics of the robot's movement was successfully captured. Note also that there was no drift in the roll and pitch estimates. Yaw angle did evolve in time, but this was because the robot was turning.

B. *Experiment 2 – Dealing with Slippage*

In Experiment 1, we have demonstrated the performance of the inertial navigation system aided by legged odometry. As a next step, we wanted to see the performance of the system when the ground changes. We have replaced the Styrofoam arena with a foil of much lower friction, where the robot starts to slip; for the case of right-turning bounding gait at 1 Hz, the stride length dropped by half, from 0.2m to 0.1m. The robot was left to run with the right-turning bounding gait for 2.5 minutes and performance of different navigation systems was tested.

1) False Position Estimates when Slipping: First, we have used the same settings as in Exp. 1 (but the experiment was longer). Whereas the dynamics was still tracked correctly (as attitude plots, not shown here, testified), this was not the case for position anymore. The legged odometer aiding significantly overestimated the stride length (by more than 50%) and this error was carried over to the inertial navigation system (where the translational movement is not observable in position), and resulted in false translational velocity and displacement estimates (RMSE 0.38 m). This is illustrated in Fig. 10; displacement is significantly overestimated compared to the real one (blue vs. green line).

[4] Note that this RMSE (root mean squared error) is calculated as average from the RMSE due to north and RMSE due to east regarding the distance in the 2D plane between the position estimate of the dead reckoning navigation system and reference (ground truth). The estimate is subject to error accumulation in heading and hence longer runs score worse under this performance criterion.

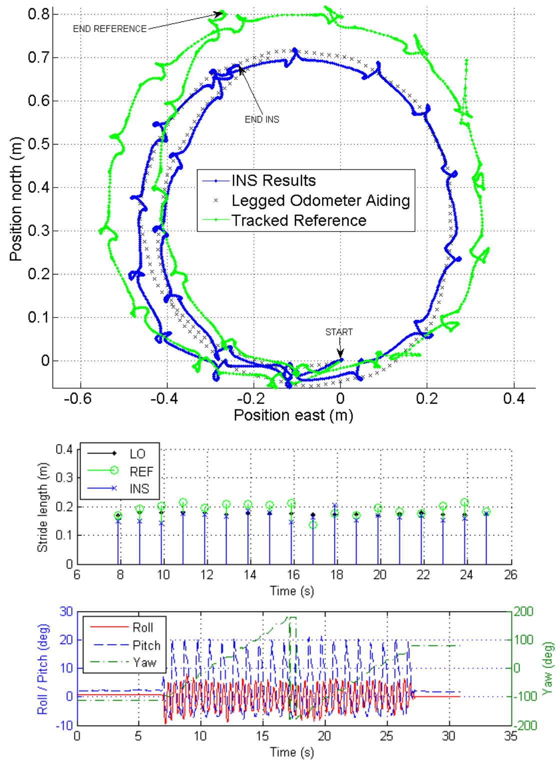

Fig. 9. Position and attitude estimation, right-turning bounding gait at 1 Hz, Styrofoam ground, 20 seconds. (Top) Real vs. estimated trajectory. Green line depicts robot trajectory as obtained from the tracking system; blue line shows the position, as estimated by the navigation system by fusing the raw inertial data with the Legged Odometer Aiding signal. Black crosses mark aiding increments from the legged odometer. Individual movement periods can be recognized by the periodic rolling movements of the COM. (Middle) Performance of stride length estimation in consecutive movement periods: legged odometer estimate (LO), reference (REF), and estimate after sensor fusion (INS). (Bottom) Attitude angles.

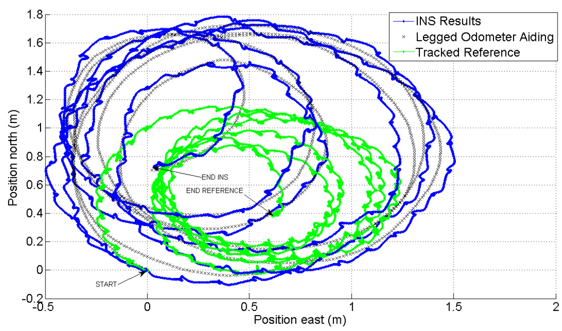

Fig. 10. Real vs. estimated trajectory, right-turning bounding gait at 1 Hz, low-friction-foil ground, 150 seconds. Styrofoam odometer was used. The translational velocity and displacement are significantly overestimated, since slippage was not detected.

2) Universal Indicator: In order to cope with the new ground conditions, we have repeated the legged odometer development (Section IV) procedure for the new ground. Afterwards, when applying the odometer version specialized for the new ground, we were able to improve the stride length estimates to less than 20% average error; the performance of the whole system also improved accordingly (RMSE 0.23 m).

However, in the end we were seeking one navigation system instance that could deal with multiple grounds. Therefore, we have included runs on both grounds into the training set (but not all frequencies) and developed a "universal" legged odometer version. On the low-friction-foil ground it achieved a comparable performance to the ground-specific version (stride length estimates error below 20%). Fig. 11 shows the performance of the whole navigation system (2.5 min., RMSE 0.22 m). This time, the estimates (blue line) show a significantly better match with the reference. We have also tested the universal odometer on the Styrofoam arena, where it delivers a two times better performance than if the odometer specialized for the other ground was used. Thus, we have shown how a single legged odometer can cope with different grounds.

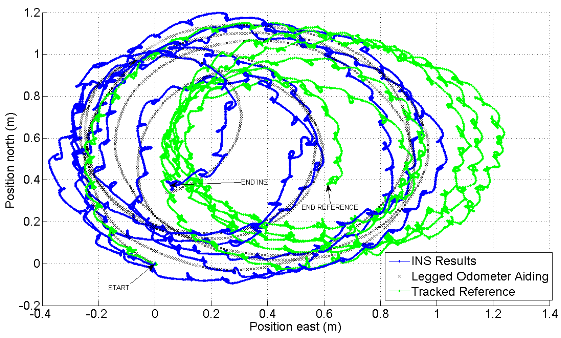

Fig. 11. Real vs. estimated trajectory, right-turning bounding gait at 1 Hz, low-friction-foil ground, 150 seconds. Ground-universal odometer was used. The translational velocity and displacement estimates are improved.

C. *Experiment 3 – Multiple Gaits*

As the last step to test the performance of our system, we have investigated a scenario where two gaits are used. Apart from the right-turning bounding gait described above, we have repeated the odometer development (Section IV) for another gait that we call "one-leg left turn", since it is dominated by the action of one (hind right) leg.

A legged odometer was trained for the one-leg left turning gait, and again relationships between the indicators and stride length were found. Moreover, universal indicators that function on the grounds with radically different friction were successfully developed. Finally, the combined system – applying the appropriate odometer version depending on the gait – was tested. Fig. 12 (top) shows the performance of the system in estimating the translational state (RMSE 0.12 m). The shift in the trajectories is to be explained by a drift in heading. The stride length estimates are satisfactory, as can also be seen in the middle part of Fig. 12. The impact of gait transition on stride length and attitude angles is shown in Fig. 12 middle, and bottom, respectively.

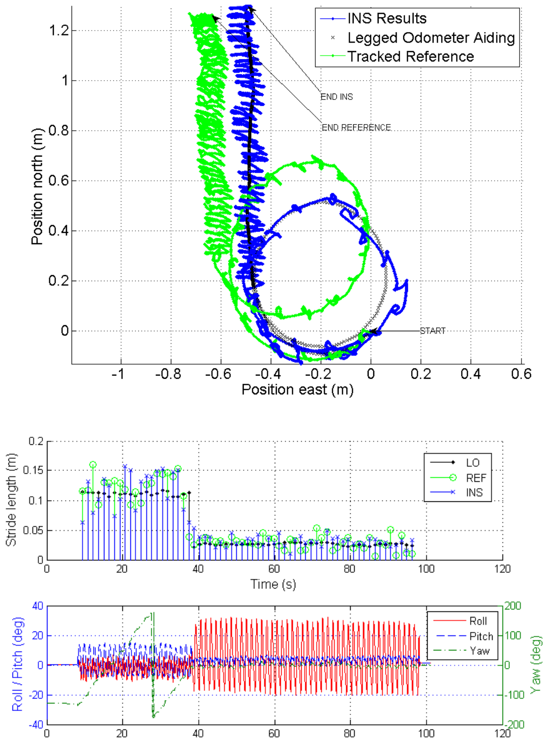

Fig. 12. Position and attitude estimation, right-turning bounding gait at 0.75 Hz, 30s, followed by one-leg left-turning gait at 0.75 Hz, 60s, on low-friction-foil ground. Universal odometers for both gaits were used. (Top) Real vs. estimated trajectory. (Middle) Performance of stride length estimation in consecutive movement periods. (Bottom) Attitude angles.

VI. Discussion, Conclusion, and Future Work

We have designed and implemented a navigation algorithm for full body state (position, velocity, and attitude) estimation for a quadruped robot. The extended Kalman filter was used to provide error estimation and data fusion from two independent sources of information: INS mechanization algorithm processing raw inertial data and legged odometry providing velocity aiding. Without using any external reference system, our architecture ensures precise tracking of a running robot's posture, and satisfactory tracking of its position over medium time intervals (final error in position of the order of one body length after a 1-2 minute run). A major contribution of this work is the development of a legged odometer. Using leg joint position sensors and feet pressure sensors we have developed a data-driven model that relates the sensory information to stride length. From the stride length estimate and the frequency of locomotion, velocity can be estimated and used for aiding.

We have successfully demonstrated how our method can cope with different velocities, terrains (different friction) and gaits. We have also successfully shown that our method generalizes to velocities that were not in the training set. We speculate that the method should also cope with grounds of different friction than the two tested. However, different gaits require separate training of the odometer.

We have discussed on the challenges that the nature of a running quadruped's locomotion poses to analytical modeling. Unlike in wheeled locomotion, all degrees of freedom are excited and individual legs, and sometimes the whole robot, loses contact with the ground. Passive compliant joints, which cannot be controlled, pose yet another difficulty. However, complex dynamics that presents itself as a difficulty to motion modeling may at the same time prove as a benefit for sensing (*sensing through body dynamics*, e.g., [32]). First, the passive compliant knee joints deliver key information for the legged odometer. It is mainly their passive nature that allows them to extract important information on the robot's interaction with the environment. If the ground friction changes, so does the trajectory of these joints. Second, we speculate that the complex nature of the legged locomotion that excites all the rotational axes adds to the performance of inertial sensing by improving the observability. This hypothesis requires further analytical and empirical treatment (see observability analysis in [4]).

Finally, we want to discuss the steps that can be taken to extend the work presented here. First, we plan to enhance the sensor suit in such a way to enable the legged odometer to aid heading information exploiting the same methodology. Second, whereas here we have demonstrated the performance of a dead reckoning system, the proposed architecture can be easily extended to include GPS or compass aiding, for instance. Third, only linear relationships (correlations) between sensory data and stride length were investigated so far. In the future, we can extend the method to nonlinear relationships, using mutual information, for instance. Fourth, the method implemented here works offline; however, we are not aware of any principle obstacle regarding an online implementation. Last but not least, the proposed method could be further elaborated and used to test hypotheses regarding the mysteries of animal navigation - in particular the combination of different self-motion (inertial, locomotor) and external cues.

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Appendix F

Using sensorimotor contingencies for terrain discrimination and adaptive walking behavior in the quadruped robot Puppy

Hoffmann, M., Schmidt, N., Pfeifer, R., Engel, A.K., and Maye, A. (2012). Using sensorimotor contingencies for terrain discrimination and adaptive walking in the quadruped robot Puppy. In Ziemke, T., Balkenius, C., and Hallam, J., editors, *From animals to animats 12: Proc. Int. Conf. Simulation of Adaptive Behavior (SAB), Odense, Denmark*, Vol. 7246 of LNAI, Springer, pages 54-64.

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Using Sensorimotor Contingencies for Terrain Discrimination and Adaptive Walking Behavior in the Quadruped Robot Puppy

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Abstract. In conventional "sense-think-act" control architectures, perception is reduced to a passive collection of sensory information, followed by a mapping onto a prestructured internal world model. For biological agents, Sensorimotor Contingency Theory (SMCT) posits that perception is not an isolated processing step, but is constituted by knowing and exercising the law-like relations between actions and resulting changes in sensory stimulation. We present a computational model of SMCT for controlling the behavior of a quadruped robot running on different terrains. Our experimental study demonstrates that: (i) Sensory-Motor Contingencies (SMC) provide better discrimination capabilities of environmental properties than conventional recognition from the sensory signals alone; (ii) discrimination is further improved by considering the action context on a longer time scale; (iii) the robot can utilize this knowledge to adapt its behavior for maximizing its stability.

Keywords: active perception, terrain recognition, object recognition, developmental robotics, adaptive behavior

1 Introduction

In the majority of approaches to robot control the extraction and classification of features from the sensory input is a crucial processing step that has a critical effect on the behavioral performance of the artificial agent. Ever more complex methods are employed to detect type and position of objects, to recognize landmarks and obstacles, or to infer the spatial configuration of the surrounding area. In mobile robotics, for example, this problem is typically solved by employing several distal (non-contact) sensors: cameras, laser range finders, and possibly also radar. Terrain classification into traversable vs. non-traversable is done in a supervised manner through a set of labeled terrain examples [1]. This is used to update an internal representation of the world – a 2D occupancy grid that in turn is used for planning a collision-free path. Although recent studies suggest that the traditional "sense-think-act" approaches can also be extended to real-world environments, their task domain is still limited.

The inherent problem of these approaches, in our view, is that they treat perception as a separate, *passive* process that is detached from the agent's actions. A "sensory snapshot" of the environment is taken that is then mapped onto the states of an internal world model. However, we believe that perception in biological agents has a different character. First, it is active. This view can be traced back to the pragmatic philosopher John Dewey [3], and it was later picked up by research in active perception (see [4] for an overview). Second, perception occurs through the body. The information that reaches the brain is thus critically shaped by the active generation of sensory stimuli and by the agent's embodiment (this is quantified in [10], for instance). Sensorimotor Contingency Theory (SMCT)[15, 14] as a representative of action-oriented approaches ascribes sensory awareness and perception to the exercise of knowledge about the lawful relations between actions and resulting changes in the sensory signals, called Sensory-Motor Contingencies (SMCs), instead of activating an internal representation of the perceived object.

We have recently developed a computational model for SMCs and demonstrated its application in an object-recognition task [11]. Here we apply the same model for controlling a robot with a completely different embodiment: a quadruped "dog" robot. We start by investigating how different gaits and terrains modulate the sensory information collected by the robot. Next we demonstrate that taking the action explicitly into account improves the terrain classification accuracy. Taking the context of longer sensorimotor sequences into account can further improve the classification performance. Finally, we show that the robot can successfully deploy its perception of the properties of different grounds to select gaits from a given repertoire to maximize its stability.

2 Related Work

The importance of sensorimotor information for object recognition in humans is evident from studies of neurological disorders [22], even though it is sometimes assigned only the role of a fall-back system [18]. In a scenario similar to ours, E.J. Gibson et al. [5] studied how infants perceive the traversability of the environment, implicitly taking into account their mode of locomotion – walking or crawling – and exploiting not only visual but also tactile information. In general, perceptual categorization in biological agents is a hard problem [7] resulting from a complex interplay of the brain, body and environment, and the individual effects are hard to separate. In this regard, robotics has provided efficient tools to test these effects independently.

First, Pfeifer and Scheier [16] have demonstrated how sensorimotor coordination can greatly simplify classification or categorization in a study where mobile robots distinguish between big and small cylinders by circling around them. Whereas this would be very difficult from a static camera picture when the distance to the object is not known, different angular velocities resulting from circling around them render the problem much easier. Similar results emerged from studies in artificial evolution: the fittest agents were those engaging in sensory-motor coordinated behavior [2].

Second, perception can be facilitated by the morphology of the body and the sensory apparatus (see examples in [8]). In legged robots that engage in different terrains, proprioceptive sensors can be particularly useful. In a previous study in our platform, we have shown how information regarding the robot's position and orientation can be extracted [17]. A combination of proprioceptive sensors has been successfully employed in a terrain recognition task in a hexapod [6].

Third, the action that caused a sensory stimulation can be explicitly taken into account in a classification task. This has been done in [19], where sensory data resulting from different actions are clustered separately. In [20], traversability categories are predefined and the robot learns – for each action separately – a mapping from initial percepts to these categories.

Many more approaches employ some form of sensorimotor information, but to our knowledge the approach we will present here is one of the few in that actions play a constitutive role for the perception of the agent as proposed by SMCT. Our method allows for a context given by the sequence of previous actions, and it is inherently multimodal. In addition, we will test the hypothesis that longer sensorimotor sequences are needed for object categorization (i.e., the ground the robot is running on in our case). Furthermore, to demonstrate the behavioral relevance of the classification capabilities for the agent, we present a closed-loop system that employs the perception of the properties of different grounds to select gaits from a given repertoire to maximize stability.

3 Methods and experiments

3.1 Robot and Experimental Setup

The Puppy robot (see Fig. 1 left) has four identical legs driven by position-controlled servomotors in the hips. It has passive compliant joints at the knees. We prepared five sets of position control commands for the servomotors, resulting in five distinct gaits (bound forwards, bound left/right, crawl, trot backwards), each of them with a periodic motor signal at 1 Hz. Four potentiometers measured the joint angles on the passive knee joints, and 4 pressure sensors recorded forces applied to the robot's feet. Linear accelerations (in X, Y, and Z direction) were measured by an onboard accelerometer. In total we used 11 sensory channels, jointly sampled at 50Hz.

To investigate the long-term properties of our approach, we additionally designed a model of Puppy in Webots [21], a physics-based simulator (see Fig. 1 right). For this model we used the same gait repertoire (2 gaits had to be adapted) plus 4 additional gaits (turn left/right, pace, walk), obtaining a repertoire of nine gaits. In both cases, gaits (actions) were exercised in 2-second-intervals during which the sensory data were collected, forming sensorimotor epochs of 2 seconds. At the end of each epoch the robot could change the gait.

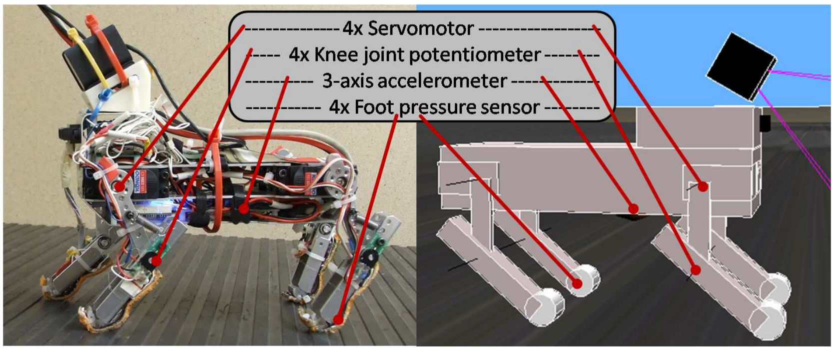

Fig. 1. Real and simulated robot and the sensor suite. The robot is 20 cm long. The camera and infrared sensors that are also mounted on the robot were not used in the experiments.

For the real robot, we prepared a small wall-enclosed arena of 2x1 m. Four different ground substrates covered the ground: plastic foil, cardboard, Styrofoam and rubber. These materials differed in friction and also in structure (cardboard and rubber had ridges). In the simulator, the arena was much bigger in size (25x25 m), so encounters with the walls were much less frequent. The “foil”, “cardboard”, and “rubber” were flat but differed in Coulomb friction coefficients ($\mu = 2$, 11, and 20 respectively). To increase the differences between the substrates in the simulator, the “Styrofoam” ground ($\mu = 9$) was made uneven with randomly placed smooth bumps of up to 3 cm height.

3.2 Feature Computation

For effective processing of sensorimotor information we compressed the raw data by extracting some simple features. For the action space we chose a high abstraction level and used the gait as a single feature. In the sensory space, following a similar strategy as we used in [17], we took advantage of the periodic nature of the locomotion and created period-based features as follows: (1) sum of knee amplitudes of all legs in a period,[3] (2) sum of standard deviations of all knee joints, (3) sum of mean pressures in each foot, (4) sum of standard deviations of each foot pressure signal, (5-7) mean accelerations along X,Y, and Z-axis respectively, (8-10) standard deviations of the accelerometer signals. Since frequent

[3] Note that the knees are passive compliant.

gait transitions disrupt the locomotion and impact also the sensory values, only the last second (i.e. the second locomotion period) from each 2s epoch was used for the feature computation. Continuous feature values were used for classification (Section 4.1); for learning the sensorimotor contingencies and optimizing the behavior using a Markov model (Section 4.2), each feature was quantized to two levels only.

3.3 A Markov Model of SMCs

We employed the model that we presented in [11, 12] with the necessary adaptations to the Puppy robot. The basic idea is to consider actions and resulting changes in sensory signals in an integrated manner, and to keep a record of sequences of actions and sensory observations. For each epoch, the action a (the gait in this case) and a vector of n sensory features observed during execution of a are concatenated to a single vector $ao(t) = [as_1 s_2 \ldots s_n]$ that we call an action-observation pair. Based on the sequence of action-observation tuples that the robot experiences over time $c^h = [ao(t), ao(t-1), \ldots ao(t-h)]$, the model samples the conditional probability distributions $P^h(ao(t+1)|c^h(t))$, i.e. the probability of experiencing a particular action-observation pair in the next time step given a finite history h of previous pairs. In this study we use $h = 0 \ldots 4$. This probability distribution is what we call the extended Sensori-Motor Contingencies (eSMC) of an agent, and a particular combination of $ao(t+1)$ and $c^h(t)$ is a specific sample that in addition to its probability of occurrence can have other properties like a value.

3.4 Value System and Action Selection

We extended the basic idea of SMCT by a value system and an action selection algorithm. For each epoch t, we define the value[4] of the robot's state by a weighted sum of three components:

$$v(t) = -tumbled - 0.4regularity - 0.1speed$$

We used the signal of the accelerometer in Z direction to determine if the robot is upright ($tumbled = 0$) or has tipped over ($tumbled = 1$). The similarity of the sensory patterns at the knee joints between the first and second period during an epoch is reflected in the *regularity* value (1 for identical patterns during both periods), and the normalized velocity computed from the robot's global coordinates yields the *speed* value.

We have devised a stochastic action selection algorithm that attempts to optimize the temporal average of the internal value. It selects actions that have shown to activate eSMCs with high internal values, and explores the consequences of new actions when no or only bad prior experiences exist in a given

[4] In reinforcement learning terms, this would be called reward - it is the immediate reward signal associated with each state.

situation. For each action-observation sequence $c^h(t)$ a record of actions executed next $a_{next}(c^h(t))$ and the average value $v(a_{next}(c^h(t)) = \sum_n v(t+1)/n$ is kept, where n is the number that action a_{next} was executed when context $c^h(t)$ was encountered, and $v(t+1)$ is the resulting value. Different history lengths h may yield different value information. Since we consider longer matches between a particular action-observation sequence and the stored eSMCs as a more accurate estimation of the state, preference is given to the value information from longer matching histories. When the robot later experiences the same context again, it knows the average value of the actions it has tried before. Random values get assigned to the other actions. To avoid a predominantly random exploration in the initial learning phase when the robot has only little sensorimotor knowledge, the expected value for the most recently executed action is given by the internal value of the last epoch. This favors the continuation of successful actions, and switching to another action otherwise. The action with the highest expected value $\hat{a} = \arg\max_a v(a_{next}(c^h(t))$ is then executed with a probability $p(\hat{a}) = v(\hat{a}) + 1$.

4 Results

4.1 Perception and Discrimination of Different Grounds

In this section, we want to quantitatively assess the effect of considering actions and the resulting changes in sensory stimulation in an integrated manner. First, we compare the respective influence of the action (the gait the robot is running with) and the environment on the sensory data. Second, focusing on the ground discrimination, we demonstrate how explicitly incorporating the action that has induced a sensory stimulation improves the environment classification. Finally, we study the effect of longer sensorimotor sequences, testing our hypothesis that these are required for object categorization, whereby, from the robot's perspective, different grounds correspond to different objects in our scenario.

We have collected data from the real (4 x 20 minutes, i.e. 4 x 600 epochs) and simulated version of the robot (4 x 4 hours, i.e. 4 x 7200 epochs) running separately on the different substrates. After every epoch a new action was chosen at random. If the robot tumbled, it was manually (real robot) or automatically (simulator) returned to an upright position at the same location and two epochs following this event were discarded. A reflex for backing up from the walls was built in. Epoches when the robot was backing up (frequent in the real robot) were not discarded but entered the regular learning process. A naïve Bayes classifier (diagonal covariance matrix estimate, stratified 10-fold cross-validation) was trained to classify either the action or the ground substrate given the sensory observations and actions during the previous epochs.

Ground and Gait Discrimination from Sensory Data Only. To assess the dependencies of the sensory signals from the gait or ground, respectively, we collapsed the data across gaits (for assessing ground effects) or across grounds (for assessing gait effects). In the real Puppy, the classifier determined the correct gait from the sensory data in 72.4% of the cases, and in 81.6% in the simulation. In contrast, the ground recognition rates were lower, 67.2% for the real Puppy and 43.1% in the simulation (see also Fig. 2, top-most bars). This shows that gaits and grounds have a similarly strong effect on the sensory patterns in the real robot. In the simulation the different materials induce similar sensory patterns and hence, are difficult to distinguish. These figures serve as a baseline when we consider the classification of joint action and sensor information next.

Ground Discrimination Using Action Information. We separated the data into sets for each gait and classified the grounds on each set individually. Afterwards we averaged the ground recognition rate over all gaits. In comparison to the ground recognition using a single classifier, the action-dependent classification schema reaches an improved accuracy of 75.7% for the real robot. Considering only the gait yielding the best recognition rate, this value increases to 80.2%. In the simulation this increase is even more pronounced, from 43.1% to 62.9% and 78.3%, respectively (see Fig. 2, second bars from top). This indicates that taking the action that caused a sensory observation into account is more specific for the environmental condition than analyzing the sensory data alone.

Ground Discrimination Using Action Sequences. The sensorimotor patterns induced by a single action may often be similar even if the agent interacts with different objects. As suggested by SMCT, longer sequences of interaction with an object may be needed in order for the object to leave a unique "footprint". We confirmed this hypothesis by splitting the data further into sets for specific sequences of 2 or 3 consecutive actions, and averaging again over all sequences. The sensory feature vectors from consecutive epochs were concatenated. For a sequence of two gaits, the ground classification accuracy rises to 84.7% in the real robot, and to 70.6% in the simulation. Considering a sequence of 3 gaits further improves accuracy (see Fig. 2). Here, the gait sequence-specific classifier with the highest accuracy achieves a 100% recognition rate. This means that the sensorimotor patterns of this action sequence are apt for a reliable recognition of the different grounds.

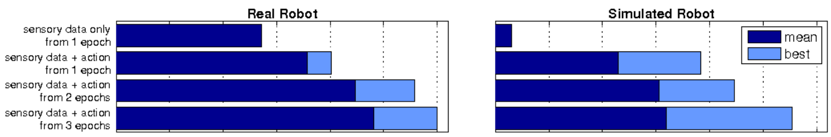

Fig. 2. Comparison of the ground classification accuracies when the action context is taken into account to different degrees. (left) Real robot. (right) Simulated robot.

4.2 Selecting Gaits to Optimize Behavior

Next we want to demonstrate how the better discrimination capabilities that result when a longer action context is considered can be used by the robot to improve its behavior. We let the simulated robot run on 4 different grounds, and used the Markov model (Sec. 3.3) to learn eSMCs for the 9 gaits from its repertoire. Each eSMC had an associated value given by the value function described in section 3.4.

With progressing sensorimotor knowledge, the robot preferred to choose gaits that improved its internal value, providing swift, smooth and stable locomotion. The plots of the value function in Fig. 3 show that a basic set of gaits that "feel good" to Puppy (i.e. maximize the value function) is found after only about 1.000 epochs (around 8 minutes). On cardboard it takes more than 2.000 epochs to arrive at a reasonable gait combination. Afterwards the robot tries to further improve its behavior by selecting from these comfortable gaits with different probabilities. As one would expect, the optimal gait sequence depends on the material properties of the grounds. Except for the plastic foil, Puppy prefers a mixture of walking back and turning left or right. It is most successful in epochs when it reduces the frequency of turns in favor of walking back. On plastic foil, the most successful gait is pacing, while turning left seems to be a less favorable gait. On cardboard, turning left is selected more frequently than turning right, though, while on rubber both turning actions are chosen with about the same frequency.

On the rough styrofoam, the value function is dominated by frequent tipping of the robot. Compared to the three flat grounds the value remains at a low level, and the separation into favorable and unpleasant gaits is less pronounced. The order of preference seems to be maintained, though.

The improvement of the internal value is not monotonic, but proceeds in a rather oscillatory manner. Intervals in which the robot had sufficient sensorimotor knowledge to optimize its behavior alternated with epochs in which it learned new eSMCs. With the sensorimotor knowledge growing, episodes with optimal behavior become more frequent and last longer. On cardboard, for example, behaviors that maximize the value function are found after about $2 \cdot 10^4$ epochs, and the increasing width of the peaks in the value function indicate that the robot spends more and more time in these optimal behaviors. A similar observation can be made on plastic foil. On rubber, the knowledge about favorable behavior around $2 \cdot 10^4$ seems to be lost afterwards, but it can be expected that the exploration process leads to a further improvement beyond the analyzed interval. Since the value function was designed to never reach zero, corresponding to a state of perfect harmony, the robot keeps on exploring the potential to further improve its fitness.

5 Conclusion and Future Work

In this study we have investigated sensorimotor classification of different substrates in a quadruped robot from the perspective of SMCT. First, we have

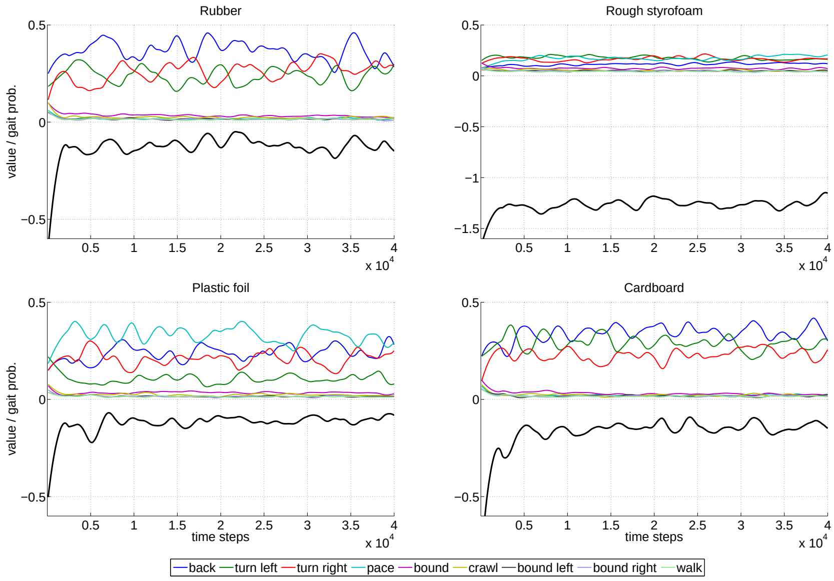

Fig. 3. Value (black curve under the abscissa) and gait selection frequencies (above) over time on 4 ground substrates (data from simulator). All curves have been smoothed with a weighted linear least squares and a 2nd degree polynomial model in a moving window of 5.000 samples. To appreciate the time course of the value function, the initially low values have been clipped. Note the different scale of the value function for rough styrofoam.

demonstrated how sensory stimulation patterns critically depend on the actions the robot is exercising. If the robot wants to recognize the object or environment it is interacting with, like the terrain type in our case, the action (gait) that gives rise to the experienced sensory stimulation needs to be considered. In addition we have shown that deployment of longer action contexts further improves the discrimination capabilities. Our approach demonstrates that the robot successfully engages the acquired sensorimotor knowledge to optimize its behavior by selecting appropriate gaits on different ground substrates.

Apart from serving as a model of SMCT, our work has also substantial application potential. Autonomous, perception-based, off-road navigation is a hot research topic in mobile robotics (e.g., [9]). Unlike traditional approaches that rely on passive long-distance perception using high resolution sensors, we have hinted at the potential of a radically different approach: terrain perception through active generation of sensory stimulation in a multimodal collection of low-resolution sensors (for learning eSMCs, 1 bit per sensory channel was used). Taking action-observation sequences into account and exploiting the robot's rich body dynamics to simplify the structure of the sensory information, an advantageous transformation of the input space for classification can be achieved.

In the current study we have employed only proprioceptive and contact sensors. These have proven very effective in ground discrimination and, in conjunction with a simple one-step prediction of the best next action based on the current sensorimotor context, the robot could optimize its behavior. However, these sensors provide little information about the terrain beyond the robot's current location. Distal sensors (like infrared or vision), on the other hand, could provide information about future events that could likewise be exploited for perceptual categorization and further improvement of the behavior. A promising approach in this respect uses internal simulation in sensorimotor space to find action sequences that optimize the success of the agent with a longer temporal horizon [13, 19]. Alternatively, reinforcement learning algorithms could be employed. Traversability in general may be a suitable touchstone to compare different approaches to use sensorimotor information for controlling robots. This will be the direction of our future work.

Acknowledgement

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Appendix G

Embodied Moving-Target Seeking with Prediction and Planning

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Embodied moving-target seeking with prediction and planning

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Abstract. We present a bio-inspired control method for moving-target seeking with a mobile robot, which resembles a predator-prey scenario. The motor repertoire of a simulated Khepera robot was restricted to a discrete number of 'gaits'. After an exploration phase, the robot automatically synthesizes a model of its motor repertoire, acquiring a forward model. Two additional components were introduced for the task of catching a prey robot. First, an inverse model to the forward model, which is used to determine the action (gait) needed to reach a desired location. Second, while hunting the prey, a model of the prey's behavior is learned online by the hunter robot. All the models are learned *ab initio*, without assumptions, work in egocentric coordinates, and are probabilistic in nature. Our architecture can be applied to robots with any physical constraints (or embodiment), such as legged robots.

Keywords: bio-inspired control; forward model; inverse model; prediction; planning; egocentric coordinates

1 Introduction

This paper deals with the problem of moving-target seeking by a mobile robot, a predator-prey scenario. This problem has been long solved in nature, hence we use bio-inspired control methods to approach it. In order to approximate the real-world conditions we use a Khepera robot model with specific physical constraints. We define a set of 10 gaits, each gait being a pair of velocities for left and right motors. This restricted repertoire of gaits helps us to approximate the context of animal behavior (our final goal is to address more complex platforms such as legged robots).

We implement a forward model, which enables the robot to learn to predict how a set of motor commands from its repertoire will influence its state in the environment [1, 2]. The robot needs to learn its own dynamics model for navigation, in accordance with its limited set of gaits. We achieve this through autonomous exploration inspired by the motor-babbling observed in infants [3].

The inverse model of the forward model is used to determine the gait needed to reach a specific location in one time-step, such as the expected relative location of the prey. If a single time-step does not suffice then a sequence of gaits is planned. The number of possible combinations of gaits increases exponentially with the length of the sequence, so that efficient heuristics are needed. Finally, the hunter learns a model of the prey's behavior online and without any prior knowledge or assumptions. This prey model is used to predict future prey locations. All models operate in egocentric (robot-centered) coordinates, without any assumptions on the action space, and incorporate uncertainty.

The combination of dynamics and uncertainty (in the robot's forward model and in prediction of prey behavior) provide a useful approximation of real-world conditions. In these conditions extensive planning is unfeasible, because algorithms need to operate in real-time and a deep plan would need to be updated too rapidly to be useful (the frame problem [4]). Instead, we begin with a bottom-up approach: Find a solution that is as reactive as possible; then add lookahead prediction and planning that is required to catch the prey. Planning is therefore added only to the extent that the combination outperforms a simple reactive architecture.

2 Learning a Forward Model in an Egocentric Coordinate System

We use a relative reference system in polar coordinates centered in the hunter robot's center of mass (Fig. 1a). Angle is measured clockwise from the robot's posteroanterior vector (PA), i.e. the hunter's heading is zero degrees. Location and heading constitute a robot's pose. For the forward model, the hunter's reference system at time t is used to express the next pose after one time-step. We indicate the heading of the hunter at time t plus one time-step as the angle that the hunter robot's PA vector subtends measured clockwise with respect to the hunter robot's PA vector at time t (Fig. 1a).

The robot needs to learn to predict the outcomes of its actions. The forward model enables this. We define the application of a specific gait for a specific amount of time as an action. The consequence of such an action is a new pose of the robot. We implement the forward model as a Bayesian network (BN), as in Demiris and Dearden [5], because BNs provide a powerful probabilistic framework in which to express the causal nature of a robot's control system. A motor command (Gait) and the observations Distance, Angle, and Heading are each represented as random variables in the BN (Fig. 1b). We use a naïve Bayes classifier, which is often quite effective even when the attribute values are not conditionally independent [6, 7].

The BN parameters (the conditional probability distributions) are learned offline from data obtained during motor-babbling (randomly applied gaits, see Fig. 1c). The data is complete, the structure of the network is known and the prior probability distribution for the gaits is uniform (gaits were applied ran-

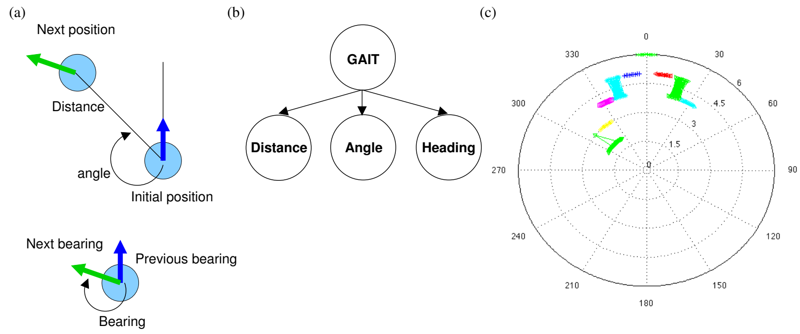

Fig. 1. (a) Egocentric coordinates. (b) Bayesian network for the forward model. (c) Plot showing the outcome of applying different gaits.

domly with equal probability). Maximum a posteriori (MAP) learning therefore reduces to maximum-likelihood parameter learning.

3 Inverse Model and Prey Model

The inverse of the forward model describes which gait to take in order to achieve a desired location (distance, angle) in one time-step. We can obtain this inverse model, $P(Gait|Distance, Angle)$, through inference from $P(Distance|Gait)$ and $P(Angle|Gait)$, which are provided by the BN of the forward model. We approximate (distance, angle) tuples with the nearest learned polar coordinates encountered during learning.

The hunter learns a probabilistic transition model of the prey's movement online, independent of the models for its own movement. The hunter observes how the prey moves, new prey pose as a function of prey pose one time-step earlier (Fig. 2a). Currently, the hunter robot gets the GPS data corresponding to the location of the prey at each time-step; at time $t+\Delta t$ (Δt being the time-step) transforms that into the prey's egocentric coordinates with respect to the prey's reference system at time t; and incorporates the egocentric coordinates to the prey model. This prey model is used to predict the prey's future positions. This approach resembles Thrun *et al.* [8], except that we make no *a-priori* assumptions about the way in which the prey moves or about its possible actions (unlike [9]). We note the frequency of each pose transition observed in terms of distance, angle and heading. An illustrative plot of a prey transition model can be seen next (Fig. 2b).

4 Models and Experiments

We develop a reactive model, a prey prediction model, and a planning model, and we assess the performance of each with the same experiment, conducted both in

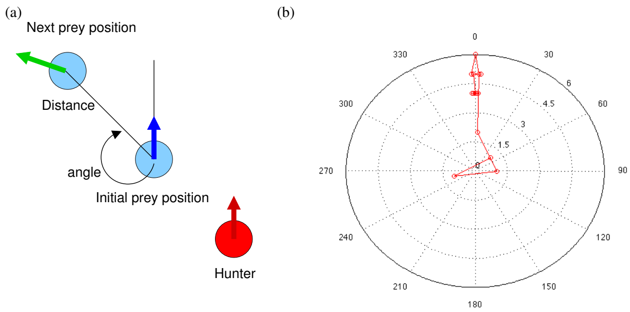

Fig. 2. (a) Illustration of one prey transition. (b) Example transition model of the prey.

a walled-in environment and in an open environment. The experiment has seven initial states. These consist in the prey being located at five bodies' distance from the hunter and with the prey at angles $\theta = 0, 1, 2, 3, 4, 5$ and 6 radians, with identical headings for hunter and prey (Fig. 3a). Cyberbotics' Webots'$^{\mathrm{TM}}$ [10] Braitenberg controller runs the prey, so that it moves straight ahead until it senses an obstacle and turns. The hunter performs no obstacle avoidance. The simulated time elapsed until the hunter catches the prey is recorded. Simulations end when the prey is caught or after one simulated minute. An experiment consists of 100 simulations for each initial state.

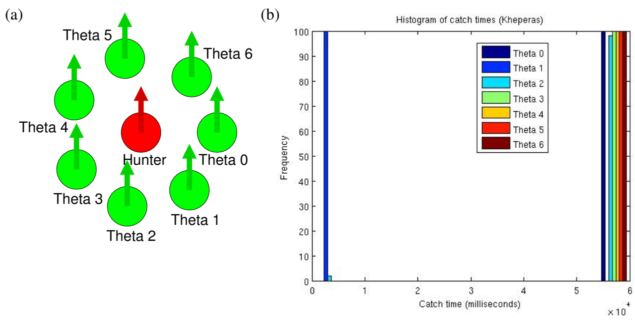

Fig. 3. (a) Experiment set-ups. (b) Results of the reactive model.

4.1 Reactive Model

The hunter applies a gait determined by the inverse model in accordance with the current prey position. Resulting reactive behavior only enables the hunter to catch the prey in very concrete circumstances. In general, the hunter appears to follow the prey around (Fig. 3b). Out of 700 runs only 102 were successful (14.57% success rate). When the prey started off at $\theta = 1$ radians the hunter was always successful. The hunter also caught the prey on 2 occasions when the prey started off at $\theta = 2$ radians.

4.2 Prey Prediction Model

The hunter learns the prey model online and uses it to predict the prey's future position (Fig. 4a). At each time-step, the prey's predicted position is used as target position for the inverse model, which determines the hunter's gait. The prey's position can be predicted ahead for a number of time-steps (T), and the optimal number depends on the distance between hunter and prey. We set T to the nearest integer to half of that distance.

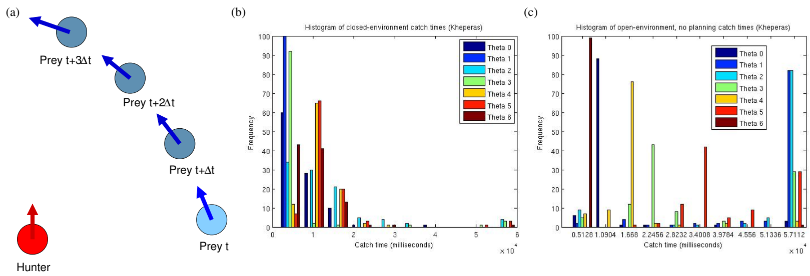

Fig. 4. (a) Prey prediction. (b) Results of the prey prediction model in the closed environment. (c) Results of the prey prediction model in the open environment.

Figure 4b shows results in a walled-in environment. The prey was caught in 655 of 700 runs (92.8% success rate), with average catch time (including misses): 15.287 seconds. Figure 4c shows results in an open environment. The prey was caught in 473 of 700 runs (67.6% success rate). The lower success rate was influenced by the prey controller, as the prey can continue to run straight when nothing forces it to turn.

4.3 Planning Model

For a better success rate in the open environment, the hunter needs to plan more than one gait ahead, composing gaits to catch the prey. We now predict the prey's position at successive time-steps and select the minimum at which a composition of gaits will minimize the distance between the hunter and the prey.

Heuristic Solution with Best-First Search: The theoretical solution would involve calculating the probability distribution for the distance between the hunter and the prey. In doing so we would encounter the "curse of dimensionality" due to the exponential increase in the size of the state space with each level of the search tree (Fig. 5). We can avoid this by using sampling to predict hunter position. We calculate samples for each time step and each different sequence of gaits. Each node in the tree has associated information: T (time-steps or depth the node plans), Gait[t] (sequence of gaits applied at time-steps $t < T$), cost in terms of number of gaits used in planning, cost in terms of number of gait transitions (transitions will be important in the legged robot scenario), Hunter[t] (predicted hunter coordinates at time-steps $t < T$ relative to hunter pose during planning), Value (final predicted distance between hunter and prey).

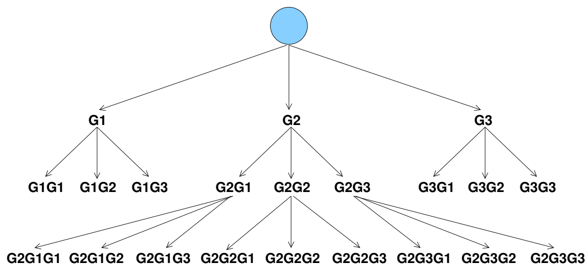

Fig. 5. Search tree for planning sequence of gaits (shown only for 3 gaits for the sake of clarity).

Choosing a sequence of gaits is a combinatorial optimization problem. A breadth-first search of the tree was too slow, so we proceeded to use a best-first search. The best-first search algorithm explores a graph by expanding the most promising node. In our case, the most promising node is the one that most reduces the distance to predicted prey position. The search tree with g^T nodes needs to be pruned further, for example by eliminating combinations with more than one gait transition. With the planning model (Fig. 6b), 591 of 700 runs were successful (84.4% success rate).

5 Discussion and Conclusions

We have presented a bio-inspired control architecture that allows a mobile robot to: (1) learn a model of its own action repertoire (a forward model); (2) learn a model of an object (prey) it is seeking; (3) combine the forward model and the prey model to seek the prey.

Braitenberg [11] and Brooks [12] showed that robots that rely on embodiment, purely reactive behaviors and that exploit interaction with the environment could address real-world dynamic problems that representations in classical

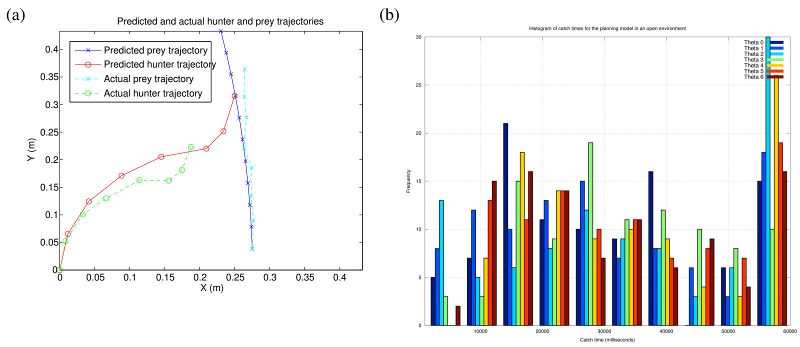

Fig. 6. (a) Example of a planning iteration. (b) Results of the planning model in an open environment.

A.I. could not adequately deal with. Such robots exhibit sophisticated behaviors and properties such as adaptivity, robustness, versatility and agility found in biological organisms, yet without emphasizing cognitive capabilities such as planning, abstract reasoning or language. Following this inspiration, we took a bottom-up approach by developing a reactive model first and only adding cognitive capabilities as and when necessary.

Our architecture has the following properties: (1) An egocentric coordinate system is used; (2) The model can deal with an arbitrary action repertoire of the hunter and the prey. There are no assumptions on the behavior of the hunter or prey; (3) The action space is discrete; (4) The models are learned *ab initio*. The hunter's forward model is is learned as a result of a motor-babbling phase. The prey's model is learned online and incrementally updated; (5) Our model accounts for and plans with uncertainty.

We see two possible uses for our architecture. First, it can be applied as a whole to moving-target seeking by an autonomous vehicle, for instance. Or, only individual components can be utilized. The forward model implementation would allow an arbitrary robot to learn its motor repertoire and plan with it. The prey model can be applied to any target object, such as in a person-following scenario [9]. Second, our scenario could serve to model biology. By adding details about particular behaviors we may test hypotheses for the way in which animals achieve similar behaviors, for example: the prey-catching behavior of the spider Portia [17] or hunting in vertebrates. At the same time, our scenario is a case for minimalistic model of cognition which is firmly grounded in body dynamics [13–16].

Future work planned includes extending our model to a legged platform which uses real gaits, adding real sensing of the prey (through a camera on the hunter, for instance), and studying various cost functions for the trajectory planning of the hunter. These can include energy consumption, or computational complexity/reaction time.

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17. Tarsitano, M.: Route selection by a jumping spider (Portia labiata) during the locomotory phase of a detour. Animal Behavior 72, 1437–1442 (2006)

Appendix H

Curriculum Vitae

Matej Hoffmann

Contact Information

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Citizenship

Czech Republic

Research Interests

Cognitive and developmental robotics, learning motor control, links between low-level sensorimotor behaviors and cognition

Education

University of Zurich,
Faculty of Economics, Business Administration and Information Technology,
Zurich, Switzerland

- Ph.D. candidate, October 2006-present
  - Thesis: From locomotion to cognition
  - Supervisor: Prof. Rolf Pfeifer
  - Areas of Study: Embodied Cognition, Artificial Intelligence, Robotics

Charles University, **Faculty of Mathematics and Physics**,
Prague, Czech Republic

- Mgr. (equivalent to MSc) in Computer Science, Theoretical Computer Science, Artificial Intelligence, 2000-2006
  - Final exam and MSc. thesis defense (Excellent, i.e. the highest possible grade)
  - Master thesis: Structural Coupling with Environment and its Modelling on Neural Driven Agents

University of Economics, **Faculty of International Relations**,
Prague, Czech Republic

- Bc. in Economics, International Trade, 2000-2004
  - Final exam and Bc. thesis defense (Excellent, i.e. the highest possible grade)

English College in Prague, Czech Republic

- IB (International Baccalaureate), 1998-2000
  - Score 43/45, best graduate of the year, Chairman's Award for Graduate Achievement presented by Lord Howe of Abberavon
- IGCSE (International General Certificate of Secondary Education), 1996-1998
  - with Distinction

Academic Experience

University of Zurich, Artificial Intelligence Lab, Zurich, Switzerland

- *Research and teaching assistant* — **October 2006 to present**
  - Main projects:
    - Extending sensorimotor contingencies to cognition, 2011-present
    - From locomotion to cognition, 2006-2010
  - Platforms: Walking and swimming robots with multimodal sensory information

Professional Activities

Selected publications

- M. Hoffmann, H.G. Marques, A. Hernandez Arieta, H. Sumioka, M. Lungarella & R. Pfeifer (2010). Body schema in robotics: a review. IEEE Transactions on Mental Development 2(4):304–24.
- M. Hoffmann & R. Pfeifer (2011). The implications of embodiment for behavior and cognition: animal and robotic case studies, in W. Tschacher & C. Bergomi, ed., 'The Implications of Embodiment: Cognition and Communication', Exeter: Imprint Academic, pp. 31-58.
- M. Hoffmann, N. Schmidt, R. Pfeifer, A.K. Engel, & A. Maye (2012). Using sensorimotor contingencies for terrain discrimination and adaptive walking in the quadruped robot Puppy. In 'From animals to animats 12: Proc. Int. Conf. Simulation of Adaptive Behavior (SAB)'. [to appear]
- M. Reinstein & M. Hoffmann (2011). Dead reckoning in a dynamic quadruped robot: inertial navigation system aided by a legged odometer, in 'Proc. IEEE Int. Conf. Robotics and Automation (ICRA)', pp. 617-624.
- N. Schmidt, M. Hoffmann, K. Nakajima, R. Pfeifer (2012). Bootstrapping perception using information theory: Case studies in a quadruped robot running on different grounds. Advances in Complex Systems J. 15(6). [to appear]

Invited talks and seminars

- Invited talks at conferences and workshops
  - R. Pfeifer & M. Hoffmann. Body representation workshop, Ascona, Oct 2010.
- Invited seminars
  - Robotics, Brain and Cognitive Sciences Dpt., Italian Institute of Technology, Genova, Italy, May 2012.
  - Bio-Robotics Network Zurich, ETH Zurich, Switzerland, April 2012.
  - 3rd International Brush-up School of GCOE: Cognitive Neuroscience Robotics, Osaka University, Japan, Nov 2011.
  - Computational Neuroscience Labs, ATR, Japan, Oct 2011.
  - Hosoda laboratory, Osaka University, Japan, Oct 2011.
  - Life and Mind seminar, Tokyo University, Japan, Oct 2011.
  - Artificial beings seminar, Charles University, Prague, Czech Rep., Dec 2008.

Teaching and educational activities

- Teaching assistance
  - ShanghAI lectures, Fall 2011
    - A global lecture series on natural and artificial intelligence with 15 participating universities.
  - Formal Methods For Computer Science - Fall 2006, 2007, 2008
  - Neural Nets, Spring 2008
- Thesis supervision and co-supervision
  - Hagmann, E. (2010). A simplified approach towards legged locomotion. (MSc. thesis)
  - Meuris, R. (2008). Sensory-motor coordination on different platforms. (MSc. thesis)

- Nuesch, S. (2009). Hopf oscillator with sensory feedback for adaptive robot locomotion. (MSc. thesis)
- Hutter, S. (2009). Co-evolution of morphology and controller of a simulated underactuated quadruped robot using evolutionary algorithms. (Bc. thesis)
- Faessler, U. and Ruegg, N. (2009). A robot learning to walk. (Bc. thesis)

- Educational materials
  - I have co-authored an online Tutorial on Embodiment that is hosted on the EU Cognition II website (http://eucognition.org).

Involvement in European projects

- Extending sensorimotor contingencies to cognition, 2011-today
- Locomorph, 2009-today
- European Network for the Advancement of Artificial Cognitive Systems, Interaction and Robotics - EU COG II & III, Coordination Council Member, 2010-today

Funding record

- Instrumental participation in the writing of the successful Grant application for the Swiss National Science Foundation project From locomotion to cognition (Grant Nr. 200020-122279, Project duration: 2 years, 2008-2010).
- Participation in the writing of the successful Grant application for the European Commision funded project Extending sensorimotor contingencies to cognition (FP7 ICT Nr. 270212, Project duration: 4 years, 1.1.2011-31.12.2014).

Reviewing work

- Reviewer for the following Journals and Conferences: Adaptive Behavior, Advances in Complex Systems, Robotics and Autonomous Systems, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE International Conference on Rehabilitation Robotics (ICORR), European Conference on Artificial Life (ECAL), IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BIOROB), International Conference on Morphological Computation (ICMC).

Organization of workshops, conferences

- Member of the Coordination Council of 2nd European Network for the Advancement of Artificial Cognitive Systems, Interaction and Robotics - EU COG II - a network action to foster the community in artificial cognitive systems in Europe.
- Co-organization of the Second EU COG II Members Conference on Development of cognition in artificial agents, Zurich, 2010 (more than 150 participants).
- Member of the organizing committee of the Bio-Robotics Network in Zurich (BiRONZ).

Media appearances, dissemination, special events

- Exhibitions
  - Shanghai Science and Art Exhibition, China (14. - 20. 5. 2009)
  - Tag der Informatik (Computer Science Day), Zurich, Switzerland (29.8.2008)
  - 175th anniversary of University of Zurich, Zurich, Switzerland (5. 4. 2008)
- Television
  - TV documentary: The robots' intelligence (NZZ Format, Swiss TV, 8. 4. 2010)
  - Inventions TV interview with Rolf Pfeifer (May 2008)

Technical Skills

Robotic platforms: Legged and swimming robots, real and simulated (Webots (ODE), Matlab SimMechanics)

Machine Learning: Artificial Neural Networks, Evolutionary Computation, Bayesian networks

Programming Languages: C/C++, Matlab, Java, Delphi, Prolog

Document production tools: Latex, MS Word, Docbook

Operating Systems: Linux, MS Windows, Mac OS (elementary)

Awards

- Creativity and Innovation Award
  - Swiss pavilion at Shanghai Science and Art Exhibition, China, 2009
- Chairman's Award for Graduate Achievement presented by Lord Howe of Abberavon
  - Award for the graduate with the highest International Baccalaureate (IB) score

References

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Dept. of Multimedia Engineering
Graduate School of Information Science and Technology
Osaka University
Email: koh.hosoda@ist.osaka-u.ac.jp

Languages

- **Czech:** mother tongue
- **English:** fluent
- **German:** fluent
  - Zentrale Oberstufenprüfung (ZOP - Göthe-Zertifikat C2) - sehr gut.
- **French:** basic